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The Industry expertise of sell-side equity analysts

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THE INDUSTRY EXPERTISE OF SELL-SIDE EQUITY ANALYSTS

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The Industry Expertise of Sell-Side Equity Analysts

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2022

I hereby declare that this PhD dissertation is my original work and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in this dissertation.

This PhD dissertation has not been submitted for any degree in any university previously.

Matthew Louis Dearth
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Abstract

Institutional investors, the most important consumer of analyst research, consistently rank industry knowledge as the most important attribute of analysts. Despite this, little is known about how investors measure industry knowledge since analyst output which can be evaluated objectively is usually associated with firm-level outcomes such as earnings forecasts or price targets. Comprehensive data are recently available for analyst forecasts of key performance indicators ("KPIs"), firm-performance metrics specific to a particular industry. Whereas reactions to earnings forecasts and other firm-level outputs only inform us about analyst skill in firm-level predictions, stock-price reactions to forecast revisions of industry-specific KPIs can proxy for industry-specific expertise of sell-side analysts. I find that stock-price reactions to KPI forecast revisions are economically meaningful and statistically significant, even when accounting for contemporaneous stock recommendation changes and earnings forecast revisions. These reactions are stronger for KPI forecast revisions that jump over the prior consensus, and for same-store sales forecast revisions on retail stocks.

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1. Introduction

> *[Foot Locker] beat Wall Street estimates on both the top and bottom lines in the second-quarter, but same-store sales came up short…The sneaker retailer earned an adjusted earnings of $0.75 a share—$0.05 ahead of the estimate from Wall Street analysts surveyed by Bloomberg. Foot Locker also said sales increased 4.8% to $1.78 billion, edging out the $1.76 billion that was expected…The lone blemish was the 0.5% increase in same-store sales, which missed the 0.7% gain that was anticipated.*[1]

The traditional finance literature has long studied how stock prices react to company earnings and other financial measures, and analyst forecasts of those measures. The Foot Locker example above demonstrates that analyst forecasts of key performance indicators (KPIs) can be as important as regular analyst output like earnings forecasts. In this instance, despite financial results that otherwise exceeded analyst estimates, results for a KPI (same-store sales) missed analyst forecasts, contributing to a one-day decline of 9.2%[2] on a day when the S&P500 index rose.

That Foot Locker disclosed same-store sales results is not surprising. Company managers pay attention to what their industry peers disclose on a voluntary basis (Lin, Mao, and Wang, 2018). In many industries, including retail, it is standard practice for companies to voluntarily disclose incremental data on operating and other statistical measures that are important to understanding their business.[3] Representative examples include passenger load factor for airlines, same-store sales (SSS) for retail, and average revenue per user (ARPU) for telecoms (Givoly, Li, Lourie, and Nekrasov, 2019). These data are often referred to as "non-financial indicators", although recent papers have used the terms "key performance indicators"

[1] "Foot Locker beats on the top and bottom lines, but same-store sales whiff (FL)" by Ethel Jiang, *Business Insider*, August 24, 2018. Retrieved from https://markets.businessinsider.com/news/stocks/foot-locker-stock-price-earnings-beat-same-store-sales-whiff-2018-8.
[2] Stock price data retrieved from yahoo!finance (https://finance.yahoo.com).
[3] Significant differences exist across industries and countries, however. For example, a study of UK-listed firms found that KPI reporting practice was highly variable, often below regulatory guidelines, and disclosure quality was negatively associated with cost of capital (Elzahar, Hussainey, Mazzi, and Tsalavoutas, 2015).

and "KPIs" interchangeably.[4] Previous research has documented that these industry-level KPIs are an area of interest for analysts (Asquith, Mikhail, and Au, 2005; Orens and Lybaert, 2010; Smith and van der Heijden, 2017). In fact, analyst attention to KPIs may play an important role in the increased adoption of KPI disclosure within an industry, since analysts themselves influence company management to disclose this type of information (Chapman and Green, 2018).

The majority of sell-side analysts specialize in a particular industry, and focus their attention—and therefore their output—on a specific set of firms called a "coverage list" (Kadan, Madureira, Wang, and Zach, 2012). Analysts gather public and non-public information about companies on their coverage list, analyze that information, and generate insights which are shared with the broker's clients. This analyst-generated information takes several different forms, some of which is made publicly available and some of which is not (Brown, Call, Clement, and Sharp, 2015). The publicly available output includes financial forecasts, especially earnings estimates and specific financial statement line-items; investment recommendations, typically expressed as "Buy", "Hold", or "Sell"; and price targets that convey the expected return resulting from the analyst's financial forecasts. Output is disseminated to clients, and where required by regulators to the public, through mixed formats including written reports, phone calls, pages on brokerage websites, and submissions to third-party data providers. Clients then reward analysts for their performance through an internal "broker vote" that is used to allocate commissions to the brokerage firm (economic rewards), and by voting in external polls (reputational rewards) such as the annual Institutional Investor (II) survey (e.g., Fang and Yasuda, 2014).

[4]Use of the term "KPIs" has the potential to cause some confusion, however, since traditional GAAP items or ratios such as EBITDA and operating margin may also be referred to as key performance indicators. In recent guidance on the disclosure of information in the MD&A section of corporate filings, the US Securities and Exchange Commission distinguishes between 1) financial measures calculated in accordance with GAAP, and 2) operating and other statistical measures. The remainder of this paper uses the term KPI to mean operating and other statistical measures, to the exclusion of traditional financial measures.

Until 2011, the Institutional Investor survey asked investors to rank the most valuable attributes of sell-side analysts; the results consistently showed industry knowledge to be the most highly valued attribute (Bagnoli, Watts, and Zhang, 2008; Kadan et al., 2012). Importantly, Institutional Investor did not attempt to *define* what "industry knowledge" means to investors, nor did it ask survey respondents to provide a definition. As to why investors place such a high priority on industry knowledge, a survey of buy-side analysts (Brown, Call, Clement, and Sharp, 2016) shows that they rely on their sell-side analyst counterparts for industry knowledge as an input to their own investment process. Prior research has also shown that industry knowledge is an important input into the generation of earnings estimates and recommendations (Brown et al., 2015) and that analysts transmit more than just company-level information through their earnings forecasts (Chan and Hameed, 2006; Piotroski and Roulstone, 2004).

In the absence of a clear definition of industry knowledge or expertise,[5] previous research has conceptualized the topic in several ways. An early approach finds that analyst specialization (industry concentration) results in greater forecast accuracy (see Clement, 1999; Dunn and Nathan, 2005; Jacob, Lys, and Neale, 1999). Related to specialization is the concept of firm-level knowledge, including the amount of time covering a specific firm (Brown et al., 2016), though this is met with some disagreement in the literature (i.e., Jacob et al. find weaker support than Brown et al.) Following a second approach, for sell-side analysts specializing in a particular industry, several papers (Boni and Womack, 2006; Howe, Unlu, and Yan, 2009; Kadan et al., 2012) propose that industry knowledge can be observed in the analyst's ability to

[5]Dictionary definitions of expertise include "a high level of knowledge or skill" (https://dictionary.cambridge.org/dictionary/english/expertise), or "special skill or knowledge that is acquired by training, study, or practice" (https://www.collinsdictionary.com/dictionary/english/expertise). A health sciences paper states that "…to describe expertise is to identify the endowed resources, catalog the knowledge, and specify the skills of a person who is capable of performing in some domain at the very highest level, achieved by few others" (Bourne, Kole, and Healy, 2014). In using the term "expertise" I adopt the common element from these definitions that expertise represents a special level of knowledge that enables the highest level of performance, which accordingly should be of even greater value to investors.

rank-order the stocks on their coverage list. Finally, a third approach looks at prior work experience and finds that analysts with related experience before becoming an analyst (e.g., working in the food distribution industry before becoming a supermarket analyst) publish more accurate earnings forecasts, and their forecast revisions have stronger market reactions (Bradley, Gokkaya, and Liu, 2017). Consistent with these findings, investor relations officers also cite prior industry experience as a valuable attribute of analysts (Brown, Call, Clement, and Sharp, 2019).

Two additional approaches are related to this topic. First, a more indirect perspective on industry knowledge makes use of the full text of an analyst's published research reports (Asquith et al., 2005). This paper finds that information like strength of justifications is important above and beyond recommendations and earnings forecasts, though it falls short of assessing industry expertise specifically. Second, a paper by (Kadan et al., 2012) looks at the industry-level recommendations contained in many analyst firm-level reports. As they describe, for some brokerage firms the analyst firm-level recommendations ("buy") are published with an accompanying industry-level recommendation ("market-weight"). The authors find that the industry-level recommendations demonstrate *across*-industry expertise, however, the industry recommendations themselves may also reflect contributions from strategy analysts or research department-wide discussions that extend beyond the expertise of individual stock analysts.

Measuring analyst industry expertise has therefore been limited in part by the lack of objective analyst outputs which are clearly related to industry-specific knowledge. Analyst outputs which can be evaluated objectively are usually associated with firm-level outcomes such as earnings forecasts or price targets. Whereas reactions to earnings forecasts and other firm-level outputs only inform us about analyst skill in firm-level predictions, this paper proposes that stock-price reactions to forecast revisions of industry-specific KPIs are a more direct proxy for industry expertise of sell-side analysts. This approach offers several advantages to other measures. First, unlike across-industry recommendations (Kadan et al., 2012), KPI forecasts are more closely tied to the analyst's detailed understanding of the industry and completely within the control of the stock analyst. Rather than requiring sufficient knowledge of other industries to make an industry-level relative performance recommendation, KPI forecasts therefore may be better aligned with what institutional investors have in mind when rating the analyst. Additionally, KPI forecast revisions are also more directly observable than within-coverage list rankings, reducing the information processing burden on investors from a limited attention perspective. Finally, as discrete outputs KPI forecasts can be analyzed using similar techniques as other research outputs.

A great deal of prior research has studied traditional analyst work product—especially recommendations and earnings estimates—from multiple perspectives. First, the quantitative output can be compared with company disclosures (especially regulatory filings like 10-Ks and 10-Qs) to assess accuracy (e.g., Schipper, 1991; Stickel, 1992) and timeliness (e.g., Ivković and Jegadeesh, 2004), both as individual output elements (e.g., earnings estimates) and how one type of output affects the others, e.g., the interaction between recommendation changes and earnings estimate revisions (Kecskés, Michaely, and Womack, 2017). Second, researchers incorporate stock prices to measure profitability of and market reactions to the various types of analyst output for different types of firms under coverage and under different conditions (e.g., Barber et al., 2001; Gleason and Lee, 2003; Jegadeesh and Kim, 2010; Loh and Stulz, 2011; Mikhail et al., 1997; Stickel, 1995). Third, researchers combine the first two types of measures with analyst attributes like years of experience, education, geographic and cultural proximity, and broker investment banking relationships to assess analyst skill (e.g., Clement, 1999; Clement and Tse, 2003; Loh and Stulz, 2011) as well as evidence of systematic bias (e.g., Hirshleifer, Lourie, Ruchti, and Truong, 2020; Merkley, Michaely, and Pacelli, 2017).

While this paper is the first to use a large sample of analyst KPI forecasts to study analyst industry expertise, previous research has analyzed KPIs as a driver of valuation and predictor of future stock returns for individual industries. Two early studies look at the telecommunications industry: Amir and Lev (1996) explore the linkage between population, penetration rates, and market valuation, while Ittner and Larcker (1998) focus on the impact of customer satisfaction scores. Later studies examine KPIs common to airlines such as load factors and passenger safety (Behn and Riley, 1999), Internet usage in the valuation of Internet stocks (Trueman, Wong, and Zhang, 2000), and order backlog in select manufacturing industries (Rajgopal, Shevlin, and Venkatachalam, 2003). More recent papers have studied retail same-store sales (Cole and Jones, 2004; Curtis, Lundholm, and Mcvay, 2014), the value of patents in the biotech industry (Yang, 2007), and oil and gas royalty trusts (Patatoukas, Sloan, and Zha, 2015). While Francis, Schipper, and Vincent (2003) studied the explanatory power of non-GAAP metrics for three different industries (airlines, homebuilding, and restaurants), none of these papers looked at the relation between all known KPIs and firm value or stock returns. More importantly and of specific relevance to this paper, none of these studies consider an analyst's ability to forecast KPIs or the stock-price reaction to such forecasts.

Given over twenty-five years of published research on the value relevance of KPIs, what explains the relative lack of papers on KPI *forecasts* compared to other analyst outputs such as recommendations, earnings estimates, and price targets? A key issue has been data availability. Traditional financial data and analyst work product are captured and readily available from providers such as Compustat, CRSP, First Call, and Refinitiv. Until recently, neither the reported values of KPIs nor analyst forecasts of those KPIs were available in a consolidated third-party database. Instead, authors of the aforementioned studies hand-collected KPI data from company filings such as 10-Ks (Curtis et al., 2014). This manual work is no longer required, however, since I/B/E/S (Refinitiv) has recently introduced databases containing analyst KPI forecasts and company reported actuals.

As of yet only a few papers have reported using I/B/E/S KPI data (Beatty and Liao, 2021; Givoly et al., 2019).[6] The paper most closely related to this one, Givoly et al. (2019), investigates two issues of historical importance to the analyst literature, forecast accuracy and stock-price reactions. First, they find that analyst quarterly KPI forecasts are more accurate than earnings forecasts. Second, they identify a positive stock-price reaction to quarterly KPI surprises, but only around the quarterly earnings announcement date and only for groups of the most frequently forecasted KPIs.[7]

This paper extends Givoly et al. (2019) and makes two main contributions to the literature. I present the most comprehensive information available on the I/B/E/S KPI databases; my final sample is approximately four times larger and includes many industries and measures for the first time. I also establish the value relevance of these non-financial indicators by analyzing the stock-price reaction to KPI forecast revisions.

My study reveals economically meaningful and statistically significant stock-price reactions to KPI forecast revisions, even when accompanied by recommendation changes and EPS estimate revisions on the same date. First, I test the overall relationship between signed KPI forecast revisions (positive, reiterate, negative) and 3-day cumulative abnormal returns (CAR); coefficients are 24.7bps for Operational KPIs and 85.1bps for Sales KPIs, and both are highly statistically significant. Next I consider the impact of contemporaneous recommendation changes and EPS estimate revisions on the relation between KPI revisions

[6]In a survey of 168 papers on financial analysts published in top journals between 2008 and 2015, (Spence, Aleksanyan, Millo, Imam, and Abhayawansa, 2019) found that 81% focused on estimates or contents included in analyst reports, including 53% analyzed earnings forecasts, 14% stock recommendations, and 10% other estimates (e.g., target prices). Given that target prices were added to I/B/E/S in 1996, it is perhaps unsurprising that very few studies have been published thus far using KPI data.

[7]To address sample size issues, Givoly et al. (2019) select the three KPIs in each of their four industries that are most followed by analysts, construct an average of the surprises of these three KPIs, rank the average across all firm-quarters, and then assign values by tercile of the ranked averages. See Givoly et al. (2019), page 1158.

and CAR. Whenever a signed KPI forecast revision is accompanied by a recommendation change, the effect of the recommendation change is much larger than the effect of the KPI revision, but the coefficient of the KPI forecast revision remains positive and economically meaningful, showing that KPI forecasts contain incremental and valuable information for stock prices. For example, when testing the relation between signed KPI revisions with a recommendation change on the same day for the Operational KPI sample, the coefficient for the recommendation change is 237.6bps, and the KPI revision coefficient is 24.1bps versus the 24.7bps when tested without the recommendation change. A similar pattern emerges when including EPS estimate revisions alone or in combination with recommendation changes, namely that signed KPI forecast revisions add economically meaningful information above and beyond the more traditional measures of analyst output.

I also test an alternative measure of KPI forecast revisions that looks at the revision relative to consensus. In the spirit of Jegadeesh and Kim (2010) and others, I expect that revisions that jump over or below consensus will be more valuable to investors, and my analysis supports this hypothesis. For example, the relation between KPI forecast revisions relative to consensus and CAR without any other analyst outputs on the same date increases in magnitude for both samples, e.g., 38.8bps vs. 24.7bps for Operational KPIs. Additional tests incorporating simultaneous recommendation changes and EPS estimate revisions exhibit similar changes in coefficients using the relative to consensus measure of KPI forecast revisions when compared to the signed revision measure.

Finally, the relation between KPI forecast revisions and CAR is meaningfully larger in the Sales KPI sample than the Operational KPI sample across all tests. For example, when tested alone the Sales KPI revision coefficients are 85.1bps (vs. 24.7bps for Operational KPIs) for the signed revisions, and 111.6bps (vs. 38.8bps) using the relative to consensus measure. I conduct an additional test of the impact of the sign of the KPI (revenue-related vs. expense-related) on the relation between Operational KPI revisions and CAR and find no significant effect, suggesting that the strength of the Sales KPI forecast relation to CAR is not attributable only to the fact that the KPIs in that sample are sales (revenue) focused.

The rest of this paper is organized as follows. Section 2 describes the data and sample. Section 3 explains the methodology. The results of my analysis are presented in Section 4 and additional tests in Section 5. Section 6 presents my conclusions.

2. Data and Sample

2.1 Data

2.1.1 KPI forecasts

KPI forecast data are retrieved from Refinitiv's Institutional Brokers Estimate Service (I/B/E/S) via Wharton Research Data Services (WRDS). Data available from IBES have expanded beyond the initial earnings estimates data (1976) to include recommendations (1992), target prices (1996), and most recently, KPI data (Bradshaw, 2011). KPI forecast data are maintained in two different databases. The first KPI forecasts to be captured were pharmaceutical product/region-level sales (measure code "SAL"), with initial observations dating to April 2005. Same-store sales ("SSS") data for retail and restaurants followed roughly two years later, then measures for hotels and entertainment, telecom, and business/geographic segments; together these data (which I/B/E/S refers to as "product level") are recorded in the Sales KPI U.S. Detail History - Estimates file (hereafter referred to as "Sales KPIs"). All other industry KPIs (hereafter referred to as "Operational KPIs") are available in the KPI U.S. Detail History file, which has grown from a handful of measures in 2012 to include 275 different measures, the most recent additions appearing in February 2018.[8] Additionally, I/B/E/S makes separate files available containing the actual KPI values for both Sales and Operational KPIs. Since these are all relatively new datasets there is no need to compensate for historical methodology changes such as those made to the earnings detail and summary files in 2015 (Call, Hewitt, Watkins, and Yohn, 2020).

As with other I/B/E/S analyst forecast data, the decision to report KPI data to I/B/E/S is made by each individual analyst. Although analysts may be motivated to consume and forecast KPIs, not all analysts may be equally motivated to disclose them. Therefore a missing forecast on I/B/E/S by a certain analyst for a given firm and KPI measure is not a definitive indication that such a forecast was never produced. That analysts are subject to self-censoring based on private information is well documented (e.g., McNichols and O'Brien, 1997). A study by Ertimur, Mayew, and Stubben (2011) found that even though many analysts maintain forecasts, analysts who already enjoy a strong reputation may not have much incentive to publish their forecasts. If the subset of analysts with strong reputations are less likely to publish their detailed forecasts, and if these strong reputations are based in part on their observed industry expertise, then it may be that an analysis of I/B/E/S data may underestimate the true value of KPI forecasts. On the other hand, if analysts with *less* expertise are less likely to publish their forecasts, then the data may *overestimate* the value of KPI forecasts. A related study found that analysts who publish long term growth forecasts with their recommendation changes receive a stronger market response than those who don't (Jung, Shane, and Yang, 2012), arguing in favor of motivation for analysts to disclose even difficult forecasts like KPIs as a signal of effort and perhaps expertise. For purpose of this paper, I assume that the I/B/E/S

[8]Data on KPI measures are taken from Refinitiv I/B/E/S Estimates Data Measure Definition Guide, v1.0, published July 25, 2019. Retrieved from https://imp-ccg.unisg.ch/-/media/dateien/unisg/bibliothek/recherche/datenbanken/ibes_definition-guide_202011.pdf Sales KPIs are called Product Level Measures, and Operational KPIs are called Industry Level Measures. There are nine Product Level Measures and 266 Industry Level Measures. See Appendix for more information on the subset of measures used in this paper.

KPI data are a representative, unbiased sample of the unobservable total population of forecasts.[9]

I take two additional steps to prepare the I/B/E/S KPI datasets for this study. First, I remove variables in the KPI dataset that are more conventional financial-type indicators because these types of indicators also exist in the regular I/B/E/S files and are already well-studied in the literature. The Operational KPI database contains three major types of KPIs: Long Term Growth Rate and per-share measures (e.g., Dividend per Share) are coded "Level I" or "Level II", financial KPIs such as revenues and profit margin are coded "Level III" and have a sector classification of "All", and the KPIs of interest to this paper are coded "Level III KPI" and classified by specific sector (e.g., "Airlines"). In addition to industry-level Sales KPIs, the Sales KPI database also contains business-segment related KPIs for Revenue, Profit, and EBITDA. Following Givoly et al. (2019), I exclude all the Level I and II KPIs, and for the Level III KPIs I create a dummy variable (KPIflag) and manually assign a value of 0 to "All"[10] and business segment KPIs, and a value of 1 to the operational KPIs that are the focus of this paper.

Second, a subset of KPIs reflect expenses or other unfavorable conditions, e.g., cost per seat mile (CPA), exploration expense (EXP), and number of stores closed/relocated (NSC). Also following Givoly et al. (2019), I create a dummy variable (KPIsign) and assign a value of -1 for this subset of unfavorable KPI measures. Multiplying the value of the KPI forecast by KPIsign allows me to interpret these "negative" KPIs in the same way as favorable KPIs. Additional data for the final sample of non-financial KPI measures appears in the Appendix.

[9]Following prior research on LTG forecasts, I do not expect I/B/E/S coding to be the source of any systematic bias in the sample of KPI forecasts (Jung, Shane, and Yang, 2012)

[10] I include "Compensation Ratio" from the "Level III-ALL" bucket since it is important in certain financial services industries like investment banking. Excluding this KPI has no material impact on the results of this study.

2.1.2 Calculation of revisions

An Operational KPI forecast is coded as a Revision if there exists a prior forecast for the same combination of Firm-Quarter-Analyst-Measure. A Sales KPI forecast is coded as a Revision if there exists a prior forecast for the same Firm-Quarter-Analyst-Measure-Region-Product combination. In both cases I check for analysts changing firms using Estimator codes and exclude a small number of reiterations and/or duplicates that result, otherwise assuming that new analyst forecasts at a new brokerage firm represent revisions to pre-existing forecasts from the prior firm, where prior forecasts exist. I exclude stale observations defined as where there is no prior forecast from the same analyst in the past 90 days.

2.1.3 Calculation of consensus

Consensus is calculated as the average forecast value when there is more than one analyst forecast on the prior day for that Firm-Quarter-Measure (Operational KPI) or Firm-Quarter-Measure-Region-Product (Sales KPI). I treat changes in Estimator codes in the same way as in the calculation of revisions and exclude stale observations using the same criteria.

2.1.4 Potential impact of EPS estimate revisions

Earnings data were retrieved from the I/B/E/S U.S. Detail File. Since this study is focused on KPI revisions rather than KPI forecast values, I follow a similar process to calculate earnings estimate revisions as for KPI forecast revisions, described above.

2.1.5 Potential impact of recommendation changes

Stock recommendations are taken from the I/B/E/S Recommendations U.S. Detail File. Since the original ratings range from 1 ("strong buy") to 5 ("sell"), I reverse code the ratings (e.g., "strong buy" now coded 5) so that more positive recommendations are associated with higher, rather than lower, ratings. After recoding, the recommendation change (recchg_3pt), which is defined as the current rating minus the prior rating by the same analyst for the same firm-quarter, is fit to a range from -2 to +2. Following the methodology as for KPIs and earnings estimates, I define recommendation revisions using the same treatment of changes in Estimator and exclusions for stale forecasts.

2.1.6 Stock-price reaction

I use a three-day event window to measure the impact of KPI revisions on daily stock returns. Cumulative Abnormal Return (CAR) is defined as the stock return in excess of Fama-French 3-factor plus momentum benchmark returns, calculated using a two-step linear model over the three-day window (-1, +1) surrounding the forecast announcement date. CARs were calculated using the Eventus program via WRDS. Day 0 corresponds to the announcement date, with non-trading days converted to trading days using the Eventus "autodate" specification. CARs were matched to KPI forecasts on PERMNO which were linked to I/B/E/S tickers using the WRDS CRSPLINK file.[11]

2.2 Sample Construction

The details of my sample construction appear in Table 1. Initial samples are retrieved from the following I/B/E/S files accessed through WRDS: Operational KPI data from KPI U.S. Detail Estimates (DET_KPIUS, file is dated July 15, 2021, which corresponds to the date of the most recent observation in each file) (forecasts) and KPI U.S Actuals (ACT_KPIUS, July 15, 2021) (actuals); Sales KPI data from the KPI U.S. Sales Detail History - Estimates (DET_SALEUS, July 15, 2021) (forecasts) and KPI U.S. Sales Actuals (ACT_SALEUS, July 15, 2021) (actuals); Earnings estimate data from U.S. Detail History (DET_EPS, May 20, 2021); and Recommendations data from U.S. Detail (RECDDET, May 20, 2021).

[Table 1 about here]

[11]Links are active through December 31, 2020, according to the terms of Singapore Management University's subscription, and as a result revisions published on or after January 1, 2021, are excluded from this analysis.

Panel A reports the number of Operational KPI forecasts in the final sample after excluding non-operational KPIs, stale KPI forecasts, anonymous analysts, forecasts missing a forecast period or CUSIP, forecasts missing actuals, and keeping only the last forecast when more than one forecast was issued on the same day. Panel B reports the number of Sales KPI forecasts in the final sample after excluding duplicate forecasts, non-sales KPIs, stale KPI forecasts, anonymous analysts, forecasts missing a forecast period or CUSIP, forecasts missing or issued after actuals, and keeping only the last forecast when more than one forecast was issued on the same day. For Sales KPI forecasts conditioning on FPI=6 has the additional impact of restricting data to quarterly forecasts, excluding monthly same-store sales (SSS) forecasts which appear frequently in the raw Retail data.

Table 2 compares the data sample and research focus used in this study to Givoly et al. (2019). My final sample contains 544,056 analyst forecasts of quarterly Operational and Sales KPIs compared to 129,184 in their paper. Consistent with Givoly et al. (2019), my total figure for Firm-Qtr-KPI forecasts includes both Operational KPI and Sales KPI data (the latter of which are at the Firm-Qtr-KPI-Region-Product level). My sample also includes 15 I/B/E/S Sectors (vs. 4 for their paper), and 118 measures (vs. 28).

Importantly, while there are thousands of observations in the KPI Sales U.S. Detail History – Estimates file prior to 2012, the KPI Sales U.S. Actuals file has very limited data during that same time frame. When asked, WRDS and Refinitiv were unable to provide an explanation or remedy. Although removing the condition to match on actuals would increase the number of available Sales KPI observations, I keep this condition to maintain comparability with Givoly et al. (2019) even though this study is not concerned with forecast accuracy.

In addition to using a much larger dataset, I extend the Givoly et al. (2019) study in two important ways. Whereas their paper only tested stock-price reactions around the earnings date, I test for these effects intra-quarter when stock prices are less likely to be influenced by quarterly earnings releases. I also incorporate consensus into my analysis, including the consensus forecast value, the number of analyst forecasts included in consensus, the standard deviation of the estimates included in consensus, and finally the direction of forecast revisions relative to consensus.

[Table 2 about here]

Descriptive statistics for the sample used for this study appear in Table 3 through Table 10. Table 3 summarizes the KPI forecasts and revisions data available for each I/B/E/S sector in the Operational KPI (Panel A) and Sales KPI (Panel B) samples as described in Table 1. An Operational KPI forecast is coded as a Revision if there exists a prior forecast for the same Firm-Analyst-Measure. A Sales KPI forecast is coded as a Revision if there exists a prior forecast for the same Firm-Analyst-Measure-Region-Product.

[Table 3 about here]

I/B/E/S uses a proprietary mapping (I/B/E/S Sector), rather than a third-party sector classification scheme such as MSCI, to classify the different KPI measures for which analysts provide forecasts. For example, KPI forecasts for the company Facebook (ticker FB) are available for six different measures across three different I/B/E/S Sectors (four measures in Media and one each in Technology and Telecom). I include all non-financial KPIs (KPIflag=1, described above) for all available I/B/E/S Sectors including those for financial firms (Banking and Finance, Insurance, Real Estate), in contrast to Givoly et al. (2019) which excluded measures that "can be directly inferred from financial statements" and as a result excluded the Financial industries altogether.

Fifteen different I/B/E/S Sectors are represented in my sample. Even though all four Sales KPI I/B/E/S Sectors also appear in the Operational KPI sample, the measures are different, e.g., Retail contains eight Operational KPIs, none of which is SSS (same-store-sales) which only appears in the Sales KPI sample. Energy is the largest sector in the Operational KPI sample with the largest number of forecasts (252,560) and revisions (74,653), attributable in part to the large number of firms (307), and unique analysts (441). Pharmaceutical and Retail comprise most of the Sales KPI sample. Unique to the Sales KPI dataset is the inclusion of Region and Product data. The Region field is only populated for Pharmaceutical KPI forecasts, whereas all Sales KPI forecasts contain Product ID information. In Givoly et al. (2019), they selected the single Region/Product for each firm with the greatest number of analyst forecasts. I include all Pharmaceutical forecasts, such that the average Pharmaceutical company includes forecasts for 6.5 products and 2.2 regions. Although Telecom appears to have a higher number of products per firm, there is only one firm in that IBES Sector (Netflix). Sample data for the Top 5 Regions and Products by IBES Sector are reported in Table 6.

[Table 4 about here]

Table 4 summarizes the KPI forecasts and revisions data available for each forecast period year in the Operational KPI (Panel A) and Sales KPI (Panel B) samples. The first observations in the Operational KPI sample appear in 2012 and reach a relatively consistent number of forecasts and revisions as of 2014. The average firm in this sample has forecasts for roughly four unique measures from over five unique analysts, resulting in approximately 16 forecasts and four revisions per firm-measure.

In the Sales KPI sample the first observations date to 2006, but with very limited numbers due to the requirement to match on actuals as described above. Firms do not appear in more than one I/B/E/S Sector in the sample, and since each I/B/E/S Sector contains only one measure, there is only ever one measure per firm. The number of unique analysts per firm ranges from roughly 5 to 11 through the sample, resulting in up to 75 forecasts and 14 revisions per firm measure.

[Table 5 about here]

Table 5 summarizes the KPI forecasts and revisions data by I/B/E/S Sector and Forecast Period Year. This cross-sectional view reveals the timing when different sectors appear in the samples from the respective datasets subject to the exclusions described in Table 1. In the Operational KPI sample the first forecasts from three I/B/E/S Sectors are available in 2012. Five more first appear in 2013, another two in 2014, and finally four more I/B/E/S Sectors in 2017. In the Sales KPI sample, as described earlier, Pharmaceuticals data begin in 2006, followed by Retail in 2012 and then Hotels and Entertainment and Telecom in 2018.

[Table 6 about here]

KPI forecast and revisions data for each I/B/E/S Sector by Measure are summarized in Table 6, beginning with the Operational KPI sample in Panel A. For the Sales KPI sample in Panel B, measures are accompanied by data for Top 5 Regions and Top 5 Products, both ranked by number of forecasts. As is seen in the Top 5 Products for Telecom (Netflix, as mentioned earlier), the Product data includes a regional component as well, e.g., "United States And Canada (ucan)". Manual inspection of the DET_SALEUS dataset reveals that while the Pharmaceuticals data appear to correctly code both Region and Product, data for the Retail sector is subject to the same issue of combined Region/Product information coded as Product.

It is unknown whether this issue originates in analyst forecasts or in how I/B/E/S captures the forecasts, but researchers who wish to analyze the I/B/E/S KPI data on a regional basis may need to take extra measures when preparing their data sample.

This study codes forecast revisions (first described in Table 3) into three categories. If the more recent forecast is greater than the prior forecast, the revision is coded as a positive revision, else it is a negative revision (less than the prior forecast) or a reiterate (no change from prior forecast). As described previously, forecasts for measures where larger values signify worse performance (e.g., expenses) are multiplied by -1 to enable comparability with measures where larger values signify better performance (e.g., revenues) (see Appendix).

[Table 7 about here]

Table 7 summarizes the number of forecast revisions by I/B/E/S Sector in the Operational KPI (Panel A) and Sales KPI (Panel B) samples. I find that across both samples there are only 420 KPI forecast reiterations out of the nearly 123,000 total revisions.[12] Non-reiteration KPI forecast revisions in both samples are split relatively evenly between positive and negative revisions. Energy accounts for 74,653 revisions out of the 99,539 total Operational KPI revisions (75%); six other I/B/E/S Sectors each have over 1,000 total revisions. The Sales KPI revision data are split roughly two-thirds Retail and one-third Pharmaceuticals; the other two I/B/E/S Sectors have only 116 revisions combined.

[Table 8 about here]

[12] Earlier research has documented the potential for incomplete data for reiterations of recommendations (see footnote 6 in Brav and Lehavy, 2003), but it is unknown if similar issues exist for KPI forecast data. However unlikely, if there were many reiterations that did not reduce the population of positive or negative revisions, they should not materially affect the significance of the KPI revisions as tested in this paper.

Similarly, Table 8 summarizes the number of forecast revisions by forecast period year. As we saw in Table 4, Operational KPI revisions (Panel A) are relatively consistently around 12,000 per year from 2014 to 2020; there are slightly more negative revisions overall, and the percentage of negative revisions by year is roughly consistent throughout the sample. In the Sales KPI sample (Panel B), the percentage of negative revisions is greater than 50% from 2012 to 2017, and less than 50% from 2018 to 2020.

Consensus is calculated as the average forecast value when there is more than one analyst forecast on the prior day for that Firm-Measure (Operational KPI) or Firm-Measure-Region-Product (Sales KPI). Figure 1 depicts the coding of positive and negative revisions (described in Table 7) relative to consensus, which is represented by the dashed line. If the initial forecast (time t) is above consensus (Panel A), the revision is coded a Jump Below if the revised forecast (time t+1) is below consensus, otherwise it is coded as No Jump. If the initial forecast is below consensus (Panel B), the revision is coded a Jump Above if the revised forecast is above consensus, otherwise it is coded as No Jump. In the case where an initial forecast is exactly equal to consensus, any revised forecast that is not a reiteration will be either a Jump Above or a Jump Below.

[Figure 1 about here]

Table 9 presents the number of forecast revisions relative to consensus by I/B/E/S Sector in the Operational KPI (Panel A) and Sales KPI (Panel B) samples. A KPI forecast is coded as a revision as described in Table 7. Revisions are coded as Jump Below, No Jump, or Jump Above as defined in Figure 1.

[Table 9 about here]

Roughly two-thirds (66.4%) of Operational KPI revisions do not cross over consensus and are coded as No Jump; for those I/B/E/S Sectors with at least 1,000 revisions, No Jump ranges from 59% (both Airlines and Banking and Finance) to 73% (Retail). Jump Below (18%) occurs more frequently than Jump Above (15%), with Jump Below ranging from 15% (Retail) to 23% (Airlines) amongst the I/B/E/S Sectors with at least 1,000 revisions. In the two dominant sectors within the Sales KPI sample, No Jump accounts for 72% of Pharmaceuticals revisions but only 49% of Retail revisions. The ratio of Jump Above to Jump Below revisions, however, are roughly the same for both of these I/B/E/S Sectors.

[Table 10 about here]

To better understand the size of the final sample that will be used to test the relation between KPI forecast revisions and stock-price reactions, Table 10 presents the number of revisions with CARs by I/B/E/S Sector in the Operational KPI (Panel A) and Sales KPI (Panel B) datasets. CARs are available for 95.1% of the Operational KPI revisions but only 87.8% of the Sales KPI revisions due in large part to missing CRSP-I/B/E/S link data as described above.

The table also shows the prevalence of recommendation changes and EPS forecast revisions for the KPI forecast revisions with CAR information. As might be expected given the long forecast horizon for recommendations, forecast revisions with CARs only share an announcement date with a recommendation change from the same analyst between 1.8% (Retail) and 2.6% (Operational) of the time. It is far more common for analysts to publish an EPS forecast revision on the same day as a KPI revision, but the degree of coincidence varies from 65% of Operational KPI forecast revisions to only 25% of Sales KPI forecast revisions.

3. Methodology

When analysts revise their recommendations, EPS estimates, or price targets, earlier studies have shown that their revisions often lead to a significant change in stock prices (e.g., Ivković and Jegadeesh, 2004). Therefore, if investors perceive analyst KPI forecasts as valuable, my hypothesis is that forecast revisions may also be accompanied by significant stock-price reactions. However, other studies have shown that analysts underreact to information in certain KPIs (Simpson, 2010), and that production of KPI forecasts does not lead to an improvement in earnings estimate accuracy (Givoly et al., 2019). In addition, just as analysts' earnings forecasts appear to piggyback on publicly disclosed company news (Altınkılıç and Hansen, 2009), so too might analysts piggyback on company disclosure of KPIs. To determine which of these conflicting findings may apply to KPIs, I analyze the relation between KPI forecast revisions and stock-price reactions using an event-study methodology following Givoly et al. (2019). My dependent variable is the 3-day cumulative abnormal return (CAR), as described above.

I test two different measures of KPI revisions, the first of which captures the sign of the revision. As important inputs to the research process, it is possible that KPI forecasts are more likely to be revised when the analyst is making a directional call. In particular, negative revisions may be more informative (Asquith et al., 2005; Frankel, Kothari, and Weber, 2006). A study by Barker and Imam (2008) found that non-accounting-based information was used more frequently when analysts wanted to express a directional view on earnings quality. While that study did not specifically reference KPIs as non-accounting-based information, as non-financial indicators KPIs fit into that category. For forecast revisions the variable *KPIrev_signed* (and its equivalent for Sales KPIs) takes a value of 1 for positive revisions, 0 for reiterates, and -1 for negative revisions as defined in Table 7.

It may be the case that KPI revisions which cross over a threshold of some level of importance may be associated with a larger stock-price reaction. A second measure of KPI forecast revisions sets this threshold based on the relation between the KPI revision and the prevailing consensus forecast, instead of using the analyst's prior forecast as a threshold. Earlier studies have documented that earnings forecast revisions that pass through consensus, either from below to above consensus or vice versa, have stronger market reactions (see Clement and Tse, 2003; Gleason and Lee, 2003; Jegadeesh and Kim, 2010). Similarly, studies of analyst recommendations found that when analysts herd towards consensus, those recommendations are less impactful (Jegadeesh and Kim, 2010; Loh and Stulz, 2011). Following the concept of "high-innovation revisions" (Gleason and Lee, 2003), I focus on those KPI revisions which jump over consensus and introduce the variable *KPIrevJump_signed* (and a similar variable for Sales KPIs). This variable takes a value of 1 for Jump Above consensus, 0 for No Jump, and -1 for Jump Below as defined in Figure 1. Note that this variable definition is not merely capturing the magnitude of the revision, i.e., a revision of certain magnitude which jumps over consensus will be coded as a Jump Above (or Below), while a revision with a larger magnitude that does not jump over consensus will be coded as No Jump. The regressions involving *KPIrevJump_signed* will also control for the magnitude of the revisions.

In the tests that follow I run two sets of models, one set (odd numbers) without controls and a second set (even numbers) including two controls. The first control variable is the number of analysts providing forecasts (*con_nanalyst*). The impact of the quantum of analyst coverage has been studied extensively in the literature. Earlier studies show a positive relation between the amount of analyst coverage and information content of earnings announcements (Beaver, McNichols, and Wang, 2018), accuracy of earnings forecasts (Merkley et al., 2017) and the speed of price adjustments to new information (Gleason and Lee, 2003). Other studies, however, find that new information may be more valuable when there is less analyst coverage and therefore a lower quality information environment (Christensen, Gomez, Ma, and Pan, 2020; Kecskés et al., 2017). In addition to the amount of coverage, I also include the standard deviation of forecasts (*con_std1dayb4*) in the consensus one day prior to the forecast revision as a second control variable. An analysis of analyst recommendations found that dispersion of prior forecasts was inversely related to analyst herding, i.e., analysts are more likely to herd when dispersion is already low (Jegadeesh and Kim, 2010). Including this control allows me to test if forecast dispersion influences the stock-price reaction to KPI revisions.

4. Results

In this section I describe the results of four sets of regression analyses, two tables each for Operational KPI and Sales KPI revisions. These pairs of tables are based on the two different measures of KPI revision described above, one using signed revisions and the other using revisions relative to consensus. In each of these four tables I run seven different models, once without controls (odd numbers) and then a second time including the two control variables (even numbers), for a total of 14 models in each table.

4.1 Signed revisions: Operational KPIs

Table 11 presents regression results for Operational KPI forecast revisions. The dependent variable is CAR as defined in Table 10. Coefficients are multiplied by 100 and presented in basis points (bps). Robust *t*-statistics are in parentheses with standard errors clustered by announcement date. Analyst and firm fixed effects are included.

Model (1) tests the relation between signed KPI revisions and CAR alone and without controls; a positive revision is associated with a CAR of 24.7bps, an economically meaningful reaction. However, analysts often publish KPI forecasts in conjunction with EPS estimates and (less frequently) stock recommendations. To understand whether KPI forecasts are incrementally informative, i.e., if the relation between KPI revision and CAR still holds in the presence of recommendation changes, EPS estimate revisions, or both, I create two additional variables, *RECrev_signed* and *EPSrev_signed*. These are coded 1, 0, or -1 following the same logic as described for *KPIrev_signed*, above. Unlike KPI revisions, however, *RECrev_signed* and *EPSrev_signed* could be missing since not all KPI revisions are accompanied by a recommendation change or EPS estimate revision. I set both variables equal to zero for observations with missing values.

Models (3), (7), and (11) test the relation between KPI revision and CAR in the presence of recommendation changes, EPS estimate revisions, or both, respectively. The coefficients for all three analyst work product variables are highly significant and positive in all three models. Across the three models the magnitude of *RECrev_signed* is roughly 10 times larger than that of *KPIrev_signed*, while *EPSrev_signed* is roughly 1.5 times larger. The coefficient of *KPIrev_signed* is approximately unchanged from Model (1) to Model (3) when it is combined with *RECrev_signed*, however the coefficient for KPI revisions drops from 24.7bps to 18.9bps (a reduction of 23%) when run with *EPSrec_signed* in Model (7). There is a reduction of similar magnitude in the coefficient for *KPIrev_signed* between Model (1), with the KPI revisions alone, and Model (11) which includes both *RECrev_signed* and *EPSrev_signed*.

If analysts have industry expertise, and since such expertise is highly valued by institutional investors, I expect KPI forecast revisions to have a positive relation with CAR. This relation should persist even if there is an accompanying recommendation change or EPS estimate revision. The regressions in Table 11 support both conjectures. The results are also consistent with the difference in the type of information contained in recommendation and earnings forecasts. That the magnitude of the coefficient on *KPIrev_signed* is roughly unchanged when there is a recommendation change on the same date is similar to earlier findings that reactions to recommendation changes are stronger when hard financial information like EPS estimates are revised as well (Kecskés et al., 2017). The reduction in the size of the KPI coefficient when there is an EPS estimate revision on the same date suggests that, while investors react to changes in KPI forecasts above and beyond the information contained in an EPS estimate revision, EPS estimate changes still elicit a stronger reaction.

[Table 11 about here]

I next consider the interaction effects between the three analyst outputs in my study. To further understand how the relation between KPI revisions and CAR changes when the KPI revision coincides with a recommendation change, I test for the interaction effect between the two. First, I create the dummy variable *RECrev_flag*, setting the dummy equal to 1 if there is a positive or negative recommendation change and 0 otherwise, including missing values. Then I calculate the interaction term *kpirev_x_rec* equal to *KPIrev_signed* * *RECrev_flag*, so that this variable will be equal to 1 when KPI revisions coincide with a recommendation change. If KPI revisions have a stronger relation when the same analyst issues a recommendation change on the same day, I would expect the coefficient for *KPIrev_signed* to remain positive and the coefficient on the interaction term to be positive as well. This interaction effect is captured in Model (5). The coefficient on *KPIrev_signed* is economically similar to Model (3), and neither the dummy variable nor the interaction term is statistically significant, suggesting that the relation between KPI revisions and CAR is the same whether or not there is a recommendation change on the same date.

I conduct a similar analysis of EPS estimate revisions, creating the variables *EPSrev_flag* and *kpirev_x_eps* and then testing the interaction effect in Model (9). The coefficient of *KPIrev_signed* falls 17%, from 18.9bps in Model (7) to 15.6bps and is only significant at the 5% level (*t*-stat 2.35). Meanwhile, the coefficient of the interaction term *kpirev_x_eps* is positive but only slightly significant (*t*-stat 1.71), suggesting that the relation between KPI revisions and CAR may be somewhat weaker in the presence of an EPS estimate revision on the same day, but it is still positive.

Finally, Model (13) tests for the impact on the relation between KPI revisions and CAR when there is both a recommendation change and an EPS estimate revision on the same day by combining the two interaction effects into one model. The coefficient of *KPIrev_signed* is 15bps compared with 18.4bps in Model (11), a similar reduction to the one between Model (9) and Model (7), and again significant only at the 5% level. The interaction terms are similar in significance and magnitude to the results of Model (5) and Model (9), providing more weak support to the positive impact of a concurrent EPS estimate revision on the relation between KPI revision and CAR. Results are similar for all models with controls.

[Table 12 about here]

4.2 Signed revisions: Sales KPIs

Table 12 presents regression results for Sales KPI forecast revisions following the same structure as for Operational KPIs in Table 11. Model (1) tests the relation between signed Sales KPI revisions (*SALESrev_signed*) and CAR without controls, showing that a positive revision is associated with a CAR of 85.1bps. That this coefficient is more than three times the Model (1) coefficient in Table 11 demonstrates that the relation between Sales KPI forecast revisions and CAR is much more strongly positive than that for Operational KPIs.

Models (3), (7), and (11) test the relation between Sales KPI revision and CAR in the presence of recommendation changes, EPS estimate revisions, or both, respectively. The coefficients for all three variables in all three models are highly significant and economically meaningful. In Model (3) the magnitude of *RECrev_signed* (396bps) is significantly larger than that of *SALESrev_signed* (82.5bps), though the Sales KPI coefficient is only 2.5bps lower than in Model (1). In Model (7) the coefficient of *EPSrev_signed* is 69.3bps, and while *SALESrev_signed* decreases nearly 10bps from Model (1) to 75.6bps, the relation between Sales KPI revisions and CAR is still stronger than that for EPS estimate revisions. When all three signed variables are included in Model (11), Sales KPI revisions still have a coefficient of 0.735, showing that the strong positive relation with CAR persists even when accompanied by recommendation changes and EPS estimate revisions.

Applying the same model structure in Table 11 to the Sales KPI sample, I test the relation between Sales KPI revisions and CAR in the presence of a recommendation change. I create the dummy variable *RECrev_flag* as before and define the interaction term *SALESrev_x_rec* equal to *SALESrev_signed* * *RECrev_flag*. This interaction effect is captured in Model (5). The coefficient on *SALESrev_signed* is economically similar to Model (3), but unlike for Operational KPIs the interaction terms contain interesting information. First, the coefficient on the interaction effect is 249bps and significant at the 1% level. The coefficient on *RECrev_flag* is negative, however, suggesting that the relation between Sales KPI revisions and CAR is stronger for negative revisions when there is a recommendation change on the same date.

I conduct a similar analysis of EPS estimate revisions, creating the variables *EPSrev_flag* and *SALESrev_x_eps* and then testing the interaction effect in Model (9). The coefficient of *SALESrev_signed* rises from 75.6bps in Model (7) to 84.8bps in the presence of an EPS estimate revision. Although the coefficient of *EPSrev_flag* is positive and slightly significant (*t*-stat 1.76), taken together this suggests that the relation between Sales KPI revisions and CAR is not meaningfully impacted by a concurrent EPS estimate revision.

Finally, Model (13) tests for the impact on the relation between Sales KPI revisions and CAR when there is a recommendation change and an EPS estimate revision on the same day by combining both sets of interaction effects into one model. The coefficient of *SALESrev_signed* increases to 82.7bps compared with 73.5bps in Model (11), suggesting that information from the Sales KPI revision is even more valuable to market participants when there is a recommendation change and EPS estimate revision released on the same date. The interaction terms are similar in significance and magnitude to the results of Model (5) and Model (9), providing more further support to the positive impact of a coincident recommendation change—and weak or no impact from an EPS estimate revision—on the relation between Sales KPI revision and CAR. Results are similar for all models with controls; the coefficients for *SALESrev_signed* are slightly larger when controls are included.

Taken together, the regressions in Tables 11 and 12 reveal significant, positive, and economically meaningful relations between signed Operational and Sales KPI revisions and stock-price reactions. These relations are robust to the occurrence of recommendation changes and EPS estimate revisions on the same day, interaction effects, and the presence of controls. Analyzing the two KPI samples separately, rather than combining them as in Givoly et al. (2019), also reveals that the relation appears stronger for Sales KPIs than for Operational KPIs (this will be further tested later in the paper). We further observe that the relation between Sales KPIs and CAR is less sensitive to the presence of other analyst work product; the magnitude of the coefficients for KPI revisions only fall 17% from high to low for Sales KPIs compared with a drop of 40% for Operational KPIs. Finally, while most of the interactions do not meaningfully affect the relation between KPI revisions and CAR, the exception is for Sales KPIs when there is a recommendation change on the same date.

4.3 Revisions relative to consensus: Operational KPIs

The second set of regressions use the alternate measure of KPI revisions, *KPIrevJump_signed*, which look at the KPI revision relative to consensus as described above. Table 13 presents regression results using this measure for Operational KPIs. The dependent variable is CAR as defined in Table 10. All other formats, controls and fixed effects are as in Table 11. Model (1) tests the relation between KPI revisions relative to consensus and CAR without controls, showing that a positive revision is associated with a CAR of 38.8bps, larger than the coefficient of 24.7bps for signed revisions as shown in Table 11, indicating a stronger stock-price reaction for revisions which jump over consensus.[13]

[Table 13 about here]

To test whether or not the relation between *KPIrevJump_signed* and CAR still holds when there other types of revisions by the same analyst on the same date, again I use the dummy variables, *RECrev_signed* and *EPSrev_signed,* as in Table 11. Models (3), (7), and (11) test the relation between KPI revision relative to consensus and CAR in the presence of recommendation changes, EPS estimate revisions, or both, respectively. Once again, the coefficients for all three variables in all three models are highly significant and positive. The magnitude of *RECrev_signed* in Model (3) is roughly the same as in the first set of regressions, 238.8bps in Table 13 compared to 237.6bps in Table 11. Similarly, the coefficients of *EPSrev_signed* in Model (7) are essentially unchanged for the two measures of KPI revisions. Changes in the coefficient of *KPIrevJump_signed* across Models (1) to (14) in Table 13 are

[13]In a separate analysis, I tested the interaction effect between *KPIrevJump_signed* on the relation between *KPIrev_signed* and CAR in both the Operational and Sales KPI forecasts regressions. The interaction is significant at the 1% level and revisions jumping over consensus contributed more than half of the magnitude of the relation between signed revisions and CAR.

very similar to those observed in Table 11. The coefficient decreases by 19%, from 38.8bps to 31.6bps, when run with *EPSrec_signed*, either alone in Model (7) or combined with *RECrev_signed* in Model (11).

I follow the same structure as in Table 11 to test the relation between *KPIrevJump_signed* and CAR in the presence of recommendation changes, EPS estimate revisions, or both. As was the case for signed KPI revisions, neither the dummy variables nor the interaction terms are statistically significant, suggesting that the relation between KPI revisions relative to consensus and CAR does not depend significantly on whether there is a recommendation change or EPS estimate revision on the same date. Results are also robust to the inclusion of controls. Importantly, the magnitude of the KPI revisions when included in the regressions as a control does not change the statistical significance of *KPIrevJump_signed*, indicating that jumping over the consensus is an important threshold effect that is independent of the magnitude of the KPI revision.

4.4 Revisions relative to consensus: Sales KPIs

The last of the four main regression tables, Table 14, uses the measure of KPI revisions relative to consensus, *SALESrevJump_signed*, for Sales KPIs. The dependent variable is CAR as defined in Table 10. All other formats, controls and fixed effects are as in Table 12. Model (1) tests the relation between KPI revisions relative to consensus and CAR without controls; the coefficient is 31% larger for the alternative measure at 111.6bps compared to 85.1bps in Table 12, further supporting the relevance of revisions relative to consensus.

[Table 14 about here]

Next, I test the relation between Sales KPI revisions relative to consensus and CAR when there are concurrent recommendation changes, EPS estimate revisions, or both, by using the dummy variables, *RECrev_signed* and *EPSrev_signed,* as in Table 12. Once again, the coefficients for all three variables in Models (3), (7), and (11) are highly significant and positive. The magnitude of *RECrev_signed* in Model (3) is roughly the same as in the first set of regressions, 408bps in Table 14 compared to 395.6bps in Table 12. The coefficient for *EPSrev_signed* increases for the alternative KPI measure used in Table 14, from 69.3bps to 81.3bps (+17%). Changes in the coefficient of *SALESrevJump_signed* across Models (1) to (14) in Table 14 are very similar in magnitude and direction to those observed in Table 12. The coefficient drops 13%, from 111.6bps to 96.1bps, but remains meaningfully positive and significant when run with *EPSrec_signed*, either alone in Model (7) or combined with *RECrev_signed* in Model (11).

I also test the relation between *SALESrevJump_signed* and CAR in the presence of recommendation changes, EPS estimate revisions, or both, following the same procedure as in Table 12. As was the case for signed KPI revisions, the interaction effects with recommendation changes shown in Model (5) and Model (13) are significant. Direction and magnitude are very similar to those in Table 12: the coefficient for the dummy variable is negative and the interaction term *SALESrev_jump_x_rec* is large (248.7bps) and statistically significant at the 1% level. The tests of signed revisions are also similar to those in Table 12 in the non-significant effect of EPS estimate changes on the relation between *SALESrevJump_signed* and CAR. Coefficients for the revisions relative to consensus are again slightly higher for the models which include controls.

The regressions in Tables 13 and 14 also show statistically significant and economically meaningful relations between Operational and Sales KPI revisions relative to consensus and stock-price reactions. Once again, the relation is significantly stronger for Sales KPIs than for Operational KPIs. Similar to the signed measure of KPI revisions, these relations are also robust to the occurrence of recommendation changes and EPS estimate revisions on the same day, interaction effects, and the presence of controls. Finally, the relation between *SALESrevJump_signed* and CAR is also influenced by recommendation changes on the same date, whereas the effects of all other interactions for both samples using the measure of revisions relative to consensus are economically and statistically insignificant.

To summarize the regression results, I plot selected regression coefficients in Figure 2 for both measures of KPI revisions with and without controls from Tables 11 to 14. Ignoring the models that include interaction effects, Figure 2 graphs the coefficients for four different pairs of models: KPI Alone (Models 1-2), KPI Controlling for Recommendation Changes (Models 3-4), KPI Controlling for EPS Revisions (Models 7-8), and KPI Controlling for Both Recommendation Changes and EPS Revisions (Models 11-12). Panels A and B show coefficients for *KPIrev_signed* and *SALESrev_signed* from Tables 11 and 12, respectively. Panels C and D show coefficients for *KPIrevJump_signed* and *SALESrevJump_signed* from Tables 13 and 14.

[Figure 2 about here]

The above analysis shows that KPI forecast revisions have a positive, statistically significant, and economically meaningful relation with stock-price reactions independent of whether the revision is measured as a simple signed revision or relative to consensus. We also find that the relation is robust to the presence of other analyst work product since the magnitude of the stock-price reaction doesn't decline meaningfully when recommendation changes, EPS estimate revisions, or both are issued by the same analyst on the same day.

Looking at the results by sample and measure of KPI revision reveals important differences. The coefficients are larger for Sales KPI revisions (Panels B and D) than for Operational KPI revisions (Panels A and C), indicating that Sales KPI revisions lead to a larger stock-price reaction regardless of which measure is used.[14] Viewed the other way, KPI revisions relative to consensus (Panels C and D) have a stronger impact on CARs than signed KPI revisions generally (Panels A and B).

5. Additional Tests

In this section I conduct two additional tests to further explore the relation between KPI forecast revisions and stock-price reactions.

5.1 Effect of KPI type

As several studies of earnings estimates and recommendations have shown, investors may have different reactions to revenue forecasts than for expenses (Beaver et al., 2018; Cheng, Chu, and Ohlson, 2020; Ertimur, Livnat, and Martikainen, 2003). To see whether this is also true for KPI forecasts, I test the relation between signed KPI revisions (*KPIrev_signed*) and CAR for Operational KPIs.[15] For this test I introduce a new variable using the hand coded dummy KPIsign described in Section II. KPIsign identifies the subset of KPIs that measure expenses or other negative conditions, e.g., cost per seat mile (CPA), exploration expense (EXP), and number of stores closed/relocated (NSC). Multiplying the value of the KPI forecast by KPIsign (coded -1 for expense-like measures, 1 otherwise) allows me to interpret these "negative" KPIs the same way as positive KPIs (see Appendix). Of the 114 measures in the Operational KPI dataset, 27 have KPIsign=-1. The dummy variable *revenue_flag* is set equal to 1 if KPIsign=1, otherwise 0.

Since I am interested in measuring the impact of KPI type on the relation between KPI revisions, I test the effect of the interaction between KPI revision and KPI type. For this

[14] Later in an additional test (5.2 Impact of I/B/E/S Sector: Retail), I show that the reaction for Retail sector KPIs is higher even for those KPIs which are included in the Operational KPI sample.
[15] Since the Sales KPI sample includes only revenue measures, it is not necessary to perform a similar test on that sample.

analysis I define the interaction variable *kpirev_x_revenue* as the product of *KPIrev_signed* and *revenue_flag*. The dependent variable is CAR and control variables are defined as in Table 11. Because there are relatively few negative KPI measures, it is possible that some firms may have no revisions with *revenue_flag* equal to zero, so I replace firm fixed effects with sector fixed effects.

[Table 15 about here]

The results of this additional test of the relation between signed KPI revisions and stock-price reaction appear in Table 15. The coefficient of *KPIrev_signed* in Model (1) without controls is 31.4bps, higher than in Table 11, and significant at the 1% level. The coefficient of *revenue_flag* is positive and weakly significant (*t*-stat 1.72), but the interaction variable is non-significant. Similar findings appear in Model (2). Based on this test I conclude that the relation between signed KPI revisions and CAR is positive, significant, and economically meaningful regardless of whether the KPI measure is revenue- or expense-related.

5.2 Impact of I/B/E/S Sector: Retail

Research on the stock-price effect of analyst output has considered a firm's industry (Drake, Jennings, Roulstone, and Thornock, 2017) and others have found that analysis needs to be at the industry level in order to capture these differences (Francis et al., 2003; Skinner, 2008). In their paper, Givoly et al. (2019) focused primarily on accuracy around quarterly releases rather than the overall relation between KPI revisions and stock-price reactions. Accordingly, they tested the relation between the average ranked surprise across the three KPIs most widely followed for each industry and CAR, finding that stock price reactions to KPI forecasts from the Retail I/B/E/S Sector were positive and highly significant.

I build on their analysis by examining the impact of KPI forecast revisions from the Retail I/B/E/S Sector on the overall relation between signed Sales KPI revisions and CAR. For this analysis I create two new variables: a dummy *retail_flag* set equal to 1 if I/B/E/S Sector is Retail, and an interaction variable *SALESrev_x_retail* as the product of *SALESrev_signed* and *retail_flag*. The dependent variable is CAR and control variables are defined as in Table 12. Because firms are included within sectors, I remove firm fixed effects and keep only analyst fixed effects.

[Table 16 about here]

Table 16 presents the results of this additional test of the relation between signed KPI revisions and CAR. The coefficient of *SALESrev_signed* in Model (1) without controls is 20.3bps and significant at the 5% level (*t*-stat 1.96). Note that this is both much lower and less significant than the Model (1) coefficient for the same measure in Table 12. The coefficient of the interaction variable *SALESrev_x_retail* is large, 100.7bps, and strongly significant (*t*-stat 6.83). Similar findings appear in Model (2); the *retail_flag* dummy is weakly significant with a negative coefficient in this model with controls. These results suggest that retail KPI revisions are responsible for much of the observed relation between signed Sales KPI revisions and CAR.

In an additional analysis, I also test whether the regression coefficients in Table 11 are different for Operational KPI forecasts in the four sectors in the Sales KPI sample (Hotels & Entertainment, Pharmaceuticals, Retail, and Telecom). The coefficients for this subset of Operational KPI forecast revisions are different than the sample as a whole, and the difference is mostly driven by the Retail sector. This suggests that forecasts of Retail sector KPIs have a larger stock-price reaction regardless of the type of KPI or whether the KPIs are reported in the Operational or Sales KPI dataset. This is consistent with the view that KPI forecasts, whether Operational or Sales KPIs, are especially important for the Retail Sector compared to other sectors.

6. Conclusion

Sell-side equity analysts provide a variety of information and services to their institutional clients, but their most valuable attribute according to investors is their industry knowledge, or expertise. Using a large sample of analyst KPI forecasts from 2012 to 2021, I show that revisions are associated with statistically significant and economically meaningful stock-price reactions. KPIs are industry-specific and important non-financial information, and this paper demonstrates that KPI forecast revisions contain market relevant information that moves stock prices. Since analyst forecasts of KPIs move the market, this presents direct, quantifiable evidence that analysts possess industry expertise.

Analyst forecasts of both Operational and Sales KPIs have positive stock-price reactions under two different formulations, both a simple signed forecast revision and a measure of forecast revision relative to consensus. These reactions are economically meaningful for signed KPI revisions, ranging from 15-25bps for Operational KPIs to 74-88bps for Sales KPIs. The revision relative to consensus is associated with even larger CARs across both Operational and Sales KPI samples, from 31-39bps and 96-116bps, respectively, consistent with findings from prior research (Clement and Tse, 2003; Gleason and Lee, 2003; Jegadeesh and Kim, 2010).

To investigate the robustness of the stock-price reactions to KPI revisions, I control for contemporaneous recommendation changes and EPS estimate revisions. I find that, as expected, recommendation changes are more impactful than either EPS estimate or KPI forecast revisions, but all three are positive under all models. The presence of a recommendation change has a large effect on the relation between Sales KPI revisions and stock-price reactions, but otherwise both types of KPI revisions are robust to the interaction effects from these analyst outputs that have been the subject of considerable prior research.

This paper makes two main contributions to the literature. First, it provides the most detailed examination of the KPI data available from I/B/E/S, extending the most closely related research on KPIs (Givoly et al., 2019) by greatly expanding the size of the data sample and evaluating intra-quarter revisions to KPI forecasts. Second, it establishes the value relevance of the I/B/E/S KPI forecast data. Whereas Givoly et al. (2019) focus on issues of accuracy, my paper uses an expanded sample of analyst KPI forecasts as a proxy for the industry expertise of sell-side equity analysts. Signed KPI forecast revisions and revisions relative to consensus are associated with statistically significant and economically meaningful stock-price reactions.

6.1 Limitations

Two methodological choices in this study could be reconsidered in future studies. First, I used Eventus to calculate CARs instead of manually calculating them from the CRSP data. I do not expect this to have a material impact on my results. Second, I did not control for the possibility that there may be KPI revisions (or recommendation changes or EPS estimate revisions) from more than one analyst for the same company on the same date. Since I study KPI forecast revisions issued before the release of quarterly results, I do not expect there to be a high degree of overlap between analyst publications and therefore limited, if any, impact on these findings.

Measuring industry expertise by studying the stock-price reaction to KPI forecast revisions complements existing research on the visible manifestations of industry expertise (recommendations, earnings estimates, price targets) but omits other, unobserved ways analysts may deliver their expertise to investors such as client-service activities (Maber, Groysberg, and Healy, 2020) like broker conferences (Green, Jame, Markov, and Subasi, 2014). Furthermore, the I/B/E/S KPI data are known to be incomplete due to disclosure restrictions imposed by the brokerage firms (anonymizing or non-disclosure of analyst IDs) and/or the analysts themselves (withholding specific types of forecasts), potentially biasing the sample. This paper assumes the I/B/E/S data are a representative sample of the true population of KPI forecasts despite the known limitations (Ertimur et al., 2011).

Another limitation of this paper is the narrow set of controls. Although I include two control variables covering different aspects of the information environment, I did not control for the contemporaneous release of other stock-related information such as 8-Ks (Zhao, 2017) or other news events (Crane and Crotty, 2020). There may also be unmeasured effects from analysts publishing revisions for multiple firms on their coverage list, either in the form of forecast bundling (Drake, Joos, Pacelli, and Twedt, 2020) or forecast fatigue (Hirshleifer, Levi, Lourie, and Teoh, 2019).

Future studies may also wish to test for analyst- or stock-level attributes that may not have been fully captured by analyst and firm fixed effects. Potential analyst-related controls could include task complexity and different measures of analyst experience, (Bradley et al., 2017; Brown et al., 2016; Clement, 1999; Mikhail et al., 1997; Orens and Lybaert, 2010). Additional stock-level control variables could include size (Cheng et al., 2020; Orens and Lybaert, 2010), trading volume (Loh, 2010), stock volatility (Kecskés et al., 2017), and institutional ownership (Cici et al., 2018; Green et al., 2014).

6.2 Future Research

The KPI data recently available through I/B/E/S offer substantial opportunities for future research. As an initial step it would be natural to further explore the relation between KPI forecasts and recommendations, earnings estimates, and price targets. One recent study finds that analyst recommendations that are less reliant on their own earnings forecasts and more reliant on other types of information are more valuable, i.e., exhibit a larger CAR (Kadan, Madureira, Wang, and Zach, 2021). On the one hand, analyst knowledge of KPIs may inform their earnings forecasts, but my paper shows the KPI forecasts have value themselves and so may be an example of more valuable non-earnings related information. To better understand this relation, future research might consider how much of the CAR from a recommendation change or EPS estimate revision is attributable to a KPI revision, in essence flipping around my design which examined how much of the KPI revision stock-price effect is due to the simultaneous issuance of other analyst output.

There also remain many opportunities to extend prior research on analyst forecasting skill to the forecasting of KPIs. This paper has documented the relation between KPI forecast revisions and CAR. In their paper, Givoly et al. (2019) found only minor improvements in earnings and revenue forecast accuracy for those analysts with KPI forecasts in the I/B/E/S database compared with those analysts without any such identifiable forecast. To further explore the channel through which investors value KPI forecasts, additional tests could investigate whether this relation arises because KPI forecasting skill is associated with other skills such as improved forecasting of cash flows, or whether investors independently value KPI forecasts as inputs into their own company models. Another strand of literature finds that analyst forecasting skills are linked to career success (Hong and Kubik, 2003; Mikhail et al., 1997); similarly, if KPI revisions are a sign of industry expertise, then KPI forecasting skill should be linked to career success proxied by All-Star rankings.

Another lens through which to evaluate the relation between analyst KPI forecasts and their decisions on what information to disseminate and how to do so. For example, a recent paper by Berger et al. (2019) explores substitutability of analyst output, where analysts may choose to revise share price targets or future quarter earnings forecasts instead of their current quarter earnings forecasts for reasons including to increase the chance for a meet-or-beat (management catering), or to avoid a revision that would move their forecast away from consensus (herding). My analysis of the I/B/E/S data finds that between 35% (Operational) and 75% (Sales) of KPI forecast revisions were not accompanied by a corresponding EPS estimate revision, so KPI forecast revisions may also serve as a substitute, allowing analysts to convey information to the market without changing their current quarter earnings forecast. When they do publish their forecasts, analysts are increasingly likely to bundle their earnings forecasts together for multiple companies on their coverage list (Drake et al., 2020). If KPI forecasts reflect a high degree of industry expertise, analysts may be likely to revise their KPI forecasts in a bundled fashion since industry-level information impacts multiple firms. Future research could test whether the findings that bundled earnings forecasts are less informative to investors extends to KPI forecasts as well.

Recent studies also suggest further ways to explore analyst industry expertise using KPI forecasts. For example, multipoint competition and mutual forbearance (Baum, Bowers, and Mohanram, 2016) illustrate what investment professionals refer to as being "the axe" in a stock—does this extend to KPIs such that an analyst might be "the axe" in a particular KPI measure for her industry? On a different note, the evidence in this paper may provide additional insight into the impact of career concerns on allocation of analyst attention and effort. Following Harford et al. (2019), if analyst forecasts are more informative for covered firms that are more important to institutional investors, significant stock-price reactions to KPI forecasts from analysts who are "the axe" in the most important names under coverage would further support the use of KPI forecasts to operationalize analyst industry expertise.

Finally, following Loh and Stulz (2011), future studies could analyze the distribution of expertise within a population of analysts by studying stock-price reactions to KPI forecast revisions at the individual analyst level. While changes in analyst IDs make it more challenging to link I/B/E/S data with Institutional Investor All-Star results, this should be possible for a limited number of high-performing analysts by hand-checking a subset of published research notes at the individual security level.

Table 1. Sample Construction

Panel A reports the number of Operational KPI forecasts in the final sample after excluding non-operational KPIs (see Section 2.1.1 for methodology, Appendix for data), stale KPI forecasts, anonymous analysts, forecasts missing a forecast period or CUSIP, forecasts missing actuals, and keeping only the last forecast when more than one forecast was issued on the same day. KPI forecasts are from I/B/E/S data file DET_KPIUS and KPI actuals from ACT_KPIUS, both with most recent observation as of July 15, 2021, and retrieved via WRDS. Panel B reports the number of Sales KPI forecasts in the final sample after excluding duplicate forecasts, non-sales KPIs (business segments), stale KPI forecasts, anonymous analysts, forecasts missing a forecast period or CUSIP, forecasts missing actuals, and keeping only the last forecast when more than one forecast was issued on the same day. Sales KPI forecasts are from I/B/E/S data file DET_SALEUS and KPI actuals from ACT_SALEUS, both with most recent observation as of July 15, 2021, and retrieved via WRDS.

Description Of Sample Construction Steps	*N Forecasts*
Panel A: Operational KPIs	
KPI forecasts available from I/B/E/S	72,856,428
Less:	
Stale KPI forecasts (issued more than 90 days before the release of the actual (FPI=6 only))	(65,195,570)
Non-operational KPIs	(7,247,862)
ANALYST=0, missing FPENDDATE, missing CUSIP	(876)
Missing actuals, forecasts issued after actuals	(13,922)
More than one forecast issued on same day (use latest only)	(509)
Final Forecast Sample	397,689
Panel B: Sales KPIs	
KPI forecasts available on I/B/E/S	5,227,038
Less:	
Duplicate forecasts	(1,031)
Non-sales KPIs	(2,205,184)
Stale KPI forecasts (issued more than 90 days before the release of the actual (FPI=6 only))	(2,728,819)
ANALYST=0, missing FPENDDATE, missing CUSIP	(1,608)
Missing actuals, forecasts issued after actuals	(144,022)
More than one forecast issued on same day (use latest only)	(7)
Final Forecast Sample	146,367

Table 2. Comparison of Sample with Givoly et al. (2019)

This table compares the research focus and data sample used in this study to the most closely related paper utilizing I/B/E/S KPI data (Givoly et al., 2019). Firm-Qtr-KPI forecasts include both Operational KPI and Sales KPI data (which are at the Firm-Qtr-KPI-Region-Product level).

	Givoly et al. (2019)	*This Study*
Primary research focus	Forecast accuracy	Stock-price reaction
Point in time	Release of actuals	All forecast dates
Main sample period	2012 to Feb 2016	2012 to May 2021
Definition of stale revisions	90 days	90 days
# Firm-Qtr-KPI forecasts	129,184	544,056
# I/B/E/S Sectors	4	15
# Measures	28	118
Intra-quarter revisions?	No	Yes
Consensus attributes? (n, std dev)	No	Yes
Revisions relative to consensus?	No	Yes

Table 3. KPI Forecasts and Revisions Available for each I/B/E/S Sector

This table summarizes the data available for each I/B/E/S sector in the Operational KPI (Panel A) and Sales KPI (Panel B) datasets, subject to the sample selection criteria described in Table 1. I/B/E/S Sector refers to the proprietary mapping used by I/B/E/S to classify the different KPI measures for which analysts provide forecasts, rather than a standard sector classification system such as MSCI. An Operational KPI forecast is coded as a Revision if there exists a prior forecast for the same Firm-Analyst-Measure. A Sales KPI forecast is coded as a Revision if there exists a prior forecast for the same Firm-Analyst-Measure-Region-Product.

Panel A: Operational KPIs

								Per Firm	
	N Unique Firms	*N Measures*	*N Forecasts*	*N Firm-Quarters*	*N KPI-Firm-Quarters*	*N Unique Analysts*	*N Revisions*	*N Unique Analysts*	*N Unique Measures*
Airlines	23	11	11,239	517	2,679	47	3,086	9.0	6.2
All	208	1	3,309	1,780	1,780	169	488	2.9	1.0
Automobiles	5	2	64	29	37	15	6	3.2	1.2
Banking and Finance	134	3	8,231	1,937	2,497	184	2,263	4.7	1.4
Energy	307	15	252,560	4,567	32,589	441	74,653	13.3	7.8
Hotels & Entertainment	39	2	1,378	249	249	57	333	5.6	1.0
Insurance	142	11	38,061	2,653	10,699	175	7,580	7.0	4.5
Media	139	10	5,115	922	1,126	292	673	6.5	1.3
Mining	89	17	5,923	999	3,017	140	659	6.0	4.8
Pharmaceuticals	2	1	12	5	5	6	0	3.0	1.0
Real Estate	197	15	18,520	1,400	5,167	187	2,770	3.5	2.4
Retail	286	8	36,691	4,183	11,456	389	5,038	8.4	3.4
Technology	227	5	10,723	1,861	2,126	360	1,188	7.9	1.3
Telecom	144	7	5,586	913	2,023	250	748	4.3	2.2
Transportation	12	6	277	92	101	19	54	3.0	1.2
Overall	1,954	114	397,689	22,107	75,551	2,731	99,539		

Panel B: Sales KPIs

	N Unique Firms	*N Measures*	*N Forecasts*	*N Firm-Quarters*	*N KPI-Firm-Quarters*	*N Unique Analysts*	*N Revisions*	*Per firm* *N Unique Analysts*	*Per firm* *N Unique Measures*	*Per firm* *N Unique Regions*	*Per firm* *N Unique Products*
Hotels & Entertainment	16	1	259	93	93	22	27	5.4	1	1.0	2.0
Pharmaceuticals	401	1	79,428	3,364	3,364	351	7,349	6.1	1	2.2	6.5
Retail	209	1	66,076	3,801	3,801	404	15,955	15.4	1	1.0	2.2
Telecom	1	1	604	11	11	32	89	32.0	1	1.0	7.0
Overall	627	4	146,367	7,269	7,269	809	23,420				

Table 4. KPI Forecasts and Revisions Available for each Forecast Period Year

This table summarizes the data available for each forecast period year in the Operational KPI (Panel A) and Sales KPI (Panel B) datasets, subject to the sample selection criteria described in Table 1. Revisions are described as in Table 3.

Panel A: Operational KPIs

						Per Firm		*Per firm-measure across all analysts*	
	N Unique Firms	*N Unique Analysts*	*N Measures*	*N Forecasts*	*N Revisions*	*N Unique Measures*	*N Unique Analysts*	*N Forecasts*	*N Revisions*
2012	96	92	13	766	70	1.4	4.3	5.9	0.5
2013	572	521	57	27,783	6,823	3.7	5.5	13.2	3.2
2014	716	692	75	49,257	12,505	4.5	5.9	15.4	3.9
2015	735	764	75	57,129	13,883	4.4	6.0	17.5	4.3
2016	712	729	86	49,943	11,394	4.4	5.9	15.9	3.6
2017	784	818	101	53,698	14,790	4.1	5.7	16.6	4.6
2018	926	940	106	54,958	13,544	3.8	5.9	15.7	3.9
2019	902	909	107	48,899	11,606	3.6	5.7	15.2	3.6
2020	888	890	97	44,813	12,676	3.4	5.5	14.8	4.2
2021	710	604	92	10,424	2,248	3.1	4.5	4.7	1.0
Overall				397,670	99,539				

Panel B: Sales KPIs

						Per Firm				*Per firm-measure across all analysts*	
	N Unique Firms	*N Unique Analysts*	*N Measures*	*N Forecasts*	*N Revisions*	*N Unique Measures*	*N Unique Analysts*	*N Unique Regions*	*N Unique Products*	*N Forecasts*	*N Revisions*
2006	1	5	1	9	3	1	5.0	1.0	1.0	9.0	3.0
2007	1	4	1	5	1	1	4.0	1.0	1.0	5.0	1.0
2008	1	7	1	21	1	1	7.0	3.0	1.0	21.0	1.0
2009	1	4	1	10	3	1	4.0	3.0	1.0	10.0	3.0
2010	1	1	1	1	0	1	1.0	1.0	1.0	1.0	0.0
2011	3	7	1	10	0	1	2.3	1.0	1.7	3.3	0.0
2012	70	185	2	1,841	343	1	6.6	1.5	4.5	26.3	4.9
2013	123	247	2	3,723	580	1	8.2	1.3	3.9	30.3	4.7
2014	177	312	2	13,235	2,453	1	10.6	1.4	4.4	74.8	13.9
2015	182	338	2	12,943	2,106	1	10.9	1.4	4.7	71.1	11.6
2016	190	330	2	11,905	1,993	1	9.6	1.4	4.7	62.7	10.5
2017	381	381	2	23,030	2,957	1	7.0	1.7	5.0	60.4	7.8
2018	448	414	4	25,238	3,423	1	6.3	1.7	4.7	56.3	7.6
2019	411	401	4	21,185	2,763	1	6.2	1.6	4.2	51.5	6.7
2020	420	399	4	25,922	5,526	1	5.8	1.7	4.1	61.7	13.2
2021	385	311	4	7,289	1,268	1	4.5	1.5	3.3	18.9	3.3
Overall				146,367	23,420						

Table 5. KPI Forecasts by I/B/E/S Sector by Forecast Period Year

This table summarizes the number of KPI forecasts available for each I/B/E/S Sector by forecast period year in the Operational KPI (Panel A) and Sales KPI (Panel B) datasets.

	2006	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*	*2018*	*2019*	*2020*	*2021*	*Total*
Panel A: Operational KPIs																	
Airlines	0	0	0	0	0	0	0	817	2,386	2,026	1,140	1,392	1,212	1,078	909	279	11,239
All	0	0	0	0	0	0	0	228	561	578	463	359	353	345	303	119	3,309
Automobiles	0	0	0	0	0	0	0	0	0	0	0	4	19	23	15	3	64
Banking and Finance	0	0	0	0	0	0	1	941	1,166	1,333	988	788	784	884	1,111	235	8,231
Energy	0	0	0	0	0	0	741	18,083	31,954	40,347	35,094	36,348	34,144	29,212	22,206	4,431	252,560
Hotels & Entertainment	0	0	0	0	0	0	0	0	0	0	0	67	392	346	459	114	1,378
Insurance	0	0	0	0	0	0	24	4,633	5,553	5,172	4,490	4,391	4,440	4,352	3,965	1,041	38,061
Media	0	0	0	0	0	0	0	0	0	0	0	149	1,246	1,382	1,915	423	5,115
Mining	0	0	0	0	0	0	0	0	113	300	594	1,082	1,074	969	1,642	149	5,923
Pharmaceuticals	0	0	0	0	0	0	0	0	1	0	0	0	0	0	9	2	12
Real Estate	0	0	0	0	0	0	0	1,065	2,815	2,490	2,115	2,896	2,506	2,035	1,957	641	18,520
Retail	0	0	0	0	0	0	0	1,981	4,171	3,911	4,059	4,989	5,615	4,659	5,673	1,633	36,691
Technology	0	0	0	0	0	0	0	37	276	322	361	473	2,277	2,637	3,327	1,013	10,723
Telecom	0	0	0	0	0	0	0	0	269	657	639	756	797	894	1,251	323	5,586
Transportation	0	0	0	0	0	0	0	0	0	0	0	4	99	83	73	18	277
Overall	0	0	0	0	0	0	766	27,785	49,265	57,136	49,943	53,698	54,958	48,899	44,815	10,424	397,689
Panel B: Sales KPIs																	
Hotels & Entertainment	0	0	0	0	0	0	0	0	0	0	0	0	81	25	137	16	259
Pharmaceuticals	9	5	21	10	1	10	1,333	1,973	5,660	5,407	5,641	14,546	15,176	11,813	14,048	3,775	79,428
Retail	0	0	0	0	0	0	508	1,750	7,575	7,536	6,264	8,484	9,902	9,158	11,455	3,444	66,076
Telecom	0	0	0	0	0	0	0	0	0	0	0	0	79	189	282	54	604
Overall	9	5	21	10	1	10	1,841	3,723	13,235	12,943	11,905	23,030	25,238	21,185	25,922	7,289	146,367

Table 6. Summary Statistics by I/B/E/S Sector by Measure

This table summarizes the data available for each Measure in the Operational KPI (Panel A) and Sales KPI (Panel B) datasets. In Panel B, Sales measures are accompanied by data for Top 5 Regions (Pharmaceutical only) and Top 5 Products, both ranked by number of forecasts. If no Region is listed the default is "WWW" for Worldwide. See the Appendix for additional information for each measure.

Measure	*Description*	*N Unique Firms*	*N Analysts*	*N Forecasts*	*N KPI-Firm-Quarters*
	Panel A: Operational KPIs				
Airlines					
ASK	Available Seat Kilometers	7	21	218	96
ASM	Available Seat Miles	17	30	1,867	386
CPA	Cost per Available Seat Miles	18	23	1,626	364
OEA	Cost per Available Seat Kilometers	7	13	128	74
PLF	Passenger Load Factor	21	37	1,942	478
PRA	Revenue per Available Seat Kilometers	7	16	158	79
PRK	Revenue per Available Seat Miles	17	25	1,799	355
RPK	Revenue Passenger Kilometers (RPK)	7	22	236	95
RPM	Revenue Passenger Miles (RPM)	15	21	1,908	366
RPP	Revenue per RPM	21	22	1,293	350
RTR	Revenue per RPK	6	13	64	36
All					
CRT	Compensation Ratio	208	169	3,309	1,780
Automobiles					
ASP	Average Selling Price	2	4	14	11
MOS	Motorcycle Shipments	4	13	50	26
Banking and Finance					
AUM	Assets Under Management	90	128	5,431	1,486
BLB	Billed Business	40	84	1,058	352
NNM	Net New Money/Assets	62	49	1,742	659
Energy					
EXP	Exploration Expense	211	232	10,214	2,255
GPD	Gas Production per Day	205	262	34,545	3,431
NPP	Natural Gas Liquids (NGL) Production per Day	164	196	21,132	2,523
OPD	Oil Production per Day	210	282	35,036	3,471
OPU	OPEX Per Unit	40	28	91	79
RPG	Realized Price - Gas	176	187	25,500	2,646
RPO	Realized Price - Oil	174	188	27,018	2,612
RZP	Realized Price (Barrell of Oil Equivalent (BOE))	141	102	6,554	1,994
TPC	Total Production Total	168	130	10,929	2,022
TPD	Total Production per Day (in BOE)	209	353	44,281	3,656
TPG	Total Production Gas	140	99	8,536	1,754
TPI	Throughput Info	39	30	903	419
TPN	Total Production NGL	120	87	4,953	1,348
TPO	Total Production Oil	146	100	7,411	1,706
TPP	Total Production per Day	160	155	15,457	2,673
Hotels & Entertainment					
ATD	Attendance	6	11	215	69
REE	Restaurant Expense	33	46	1,163	180

Panel A: Operational KPIs (cont.)

Measure	*Description*	*N Unique Firms*	*N Analysts*	*N Forecasts*	*N KPI-Firm-Quarters*
Insurance					
APE	Annual Premium Earned	2	4	20	14
CLR	Catastrophic Loss Ratio (%)	78	49	2,802	1,026
CMR	Claims Ratio (%)	7	30	196	66
COR	Combined Ratio (%)	108	110	9,172	2,081
CSL	Consolidated Loss Ratio (%)	112	86	7,300	1,872
GEP	Gross Earned Premiums	19	24	441	267
GPW	Gross Premium Written	89	79	3,209	1,278
MLR	Medical Loss Ratio (%)	16	34	910	177
NPE	Net Premiums Earned	119	133	8,333	2,219
NPW	Net Premiums Written	96	79	5,665	1,687
VNB	Value of New Business	2	2	13	12
Media					
ABP	Average Booking Per User	2	7	38	16
ARV	Advertisement Revenue	105	241	3,450	739
CPK	Cost Per Click	2	1	2	2
CPM	Cost Per Mille	1	2	6	4
DAR	Daily Active Users	13	53	567	81
GMV	Gross Merchandised Value	24	80	483	134
MAU	Monthly Active Users	20	82	498	113
MUP	Monthly Unique Payers	5	10	29	18
MUU	Monthly Unique Users	2	5	26	12
NMV	Net Merchandised Value	1	5	16	7
Mining					
ACG	All In Production Cost (AISC) - Gold	46	57	709	334
ACS	All In Production Cost (AISC) - Silver	10	15	67	51
APS	Average Price (Per Metric Tonne) - Steel	3	3	3	3
CCC	Mining Cash Cost (oz) – Copper	12	20	160	94
MCC	Mining Cash Cost (oz) - Total	54	66	653	396
MCG	Mining Cash Cost (oz) - Gold	42	54	638	308
MCS	Mining Cash Cost (oz) - Silver	10	19	130	81
MPG	Mining Production (oz) - Gold	60	96	1,633	595
MPP	Mining Production (oz) - Platinum	1	1	1	1
MPS	Mining Production (oz) - Silver	31	43	401	216
RGO	Realized Price - Gold	37	31	192	149
RPC	Realized Price – Copper	13	14	162	89
RPS	Realized Price – Silver	24	23	112	82
TMP	Mining Production (oz) - Total	56	79	546	357
TOC	Total Production – Copper (Weight)	21	42	398	182
TSE	Total Silver Equivalent Production (Weight)	9	15	76	53
USS	Unit Sales – Steel	5	3	42	26
Pharmaceuticals					
MME	Membership Enrollment	2	6	12	5
Real Estate					
BAP	Backlog Average Price	22	13	1,462	421
BGV	Backlog Values	53	45	1,502	491
BKU	Backlog Units	24	21	2,515	470
CTS	Contracted Sales	1	1	1	1
DAP	Deliveries Average Price	22	24	1,780	447
DLU	Deliveries (Number of Units)	23	25	2,322	461
DLV	Deliveries (Monetary Value)	15	20	740	286
DVC	Development Costs	68	26	166	158
HSL	Home Sales	22	28	2,059	313
LLS	Land/Lot sales	20	23	617	191
NOA	New Orders Average Price	18	14	984	358
NOU	New Orders Unit	23	25	2,140	439
NOV	New Orders Value	36	86	1,449	469
OCR	Occupancy Rate (%)	102	47	675	562
RSM	Rent per Square Foot	32	8	108	100

Panel A: Operational KPIs (cont.)

Measure	*Description*	*N Unique Firms*	*N Analysts*	*N Forecasts*	*N KPI-Firm-Quarters*
Retail					
DOS	Department Store Sales	14	13	57	32
FLF	Franchise & Licensing Fees	67	130	3,620	624
FLS	Floor Space	131	121	4,705	1,814
NAS	Net Sales per Average Square Foot	118	83	3,968	1,555
NOO	Number of Stores Opened (by Total)	144	106	2,106	1,330
NOS	Number of Stores (by Total)	227	230	12,531	3,383
NSC	Number of Stores Closed/Relocated	131	86	1,111	835
RES	Retail Sales	159	286	8,593	1,883
Technology					
BBR	Book to Bill Ratio	7	4	16	13
BIL	Billings	165	163	6,563	1,385
BKG	Bookings	93	152	1,675	486
TAC	Traffic Acquisition Cost	17	97	2,152	191
TPV	Total Payment Volume	6	52	317	51
Telecom					
ACL	Access Lines	7	12	83	59
ARP	Average Revenue Per Unit	81	168	1,696	545
CRN	Churn %	32	59	779	249
GSA	Gross Subscriber Additions	21	33	297	168
NSA	Net Subscriber Additions	87	138	1,398	477
SAC	Subscriber Acquisition Costs	5	21	60	19
SUB	Subscribers	87	164	1,273	506
Transportation					
CAK	Cargo Available Tonne Kilometers	3	3	7	6
CFR	Average Container Freight Rate	1	5	7	2
CRK	Cargo Revenue Yield Per Tonne Kilometer	1	2	5	5
RCK	Revenue Cargo Tonne Kilometers	1	2	6	5
TEU	Twenty-Foot Equivalent Units (TEU) Handled	2	3	4	4
TRL	Total Railcar Loads	7	8	248	79
Overall		6,245	7,428	397,689	75,551

Panel B: Sales KPIs

Measure	*Description*	*N Unique Firms*	*N Analysts*	*N Forecasts*	*N KPI-Firm-Quarters*
Hotels & Entertainment					
RAR	Revenue Per Available Room	16	22	259	93
	Top 5 ProductID				
	Marriott International Inc.			39	
	Hilton Worlwide Holdings Inc			35	
	Hyatt Hotels Corporation-Total			19	
	Choice Hotels Inc.			15	
	Host Hotels & Resorts Inc			14	
Pharmaceuticals					
SAL	Pharmaceutical Sales	401	351	79,428	3,364
	Top 5 ProductID				
	Tysabri			798	
	Avonex			694	
	Tecfidera			639	
	Enbrel/Brenzys			597	
	Atripla			571	
	Top 5 RegionID				
	WWW			58,546	
	US			11,224	
	WUS			6,422	
	EUR			2,496	
	JP			681	
Retail					
SSS	Same Store Sales	209	404	66,076	3,801
	Top 5 ProductID				
	Limited Brands (Consolidated)			997	
	Lululemon Athletica			878	
	Costco Wholesale Corp			844	
	Chipotle Mexican Grill Inc			802	
	Gap Inc. (Consolidated)			794	
Telecom					
GSA	Gross Subscriber Additions	1	32	604	11
	Top 5 ProductID				
	International Streaming			117	
	Domestic Streaming			115	
	Europe, Middle East, And Africa (emea)			86	
	United States And Canada (ucan)			83	
	Asia - Pacific (apac)			81	
Overall		627	809	146,367	7,269

Table 7. Revision Direction by I/B/E/S Sector

This table summarizes the number of forecast revisions by I/B/E/S Sector in the Operational KPI (Panel A) and Sales KPI (Panel B) datasets. Revisions are coded as described as in Table 3. If the more recent forecast is greater than the prior forecast, the revision is coded as a positive revision, else it is a negative revision (less than the prior forecast) or a reiterate (no change from prior forecast). Forecasts for measures where larger values signify worse performance (e.g., expenses) are multiplied by -1 to enable comparability with measures where larger values signify better performance (e.g., revenues) (see Appendix).

	Negative	*Reiterate*	*Positive*	*Total*
Panel A: Operational KPI Revisions				
Airlines	1,638	12	1,436	3,086
All	280	2	206	488
Automobiles	1	0	5	6
Banking and Finance	1,126	2	1,135	2,263
Energy	39,885	238	34,530	74,653
Hotels & Entertainment	171	0	162	333
Insurance	4,175	7	3,398	7,580
Media	304	1	368	673
Mining	349	0	310	659
Pharmaceuticals	0	0	0	0
Real Estate	1,349	1	1,420	2,770
Retail	2,643	30	2,365	5,038
Technology	618	3	567	1,188
Telecom	356	2	390	748
Transportation	35	0	19	54
Overall	52,930	298	46,311	99,539
Panel B: Sales KPI Revisions				
Hotels & Entertainment	17	0	10	27
Pharmaceuticals	3,802	53	3,494	7,349
Retail	8,160	69	7,726	15,955
Telecom	24	0	65	89
Overall	12,003	122	11,295	23,420

Table 8. Revision Direction by Forecast Period Year

This table summarizes the number of forecast revisions by forecast period year in the Operational KPI (Panel A) and Sales KPI (Panel B) datasets. Forecast revisions are defined and coded as described in Table 7.

	Negative	*Reiterate*	*Positive*	*Total*
Panel A: Operational KPI Revisions				
2012	38	1	31	70
2013	3,808	70	2,945	6,823
2014	7,059	38	5,408	12,505
2015	7,334	42	6,507	13,883
2016	5,621	77	5,696	11,394
2017	8,086	22	6,682	14,790
2018	7,253	6	6,285	13,544
2019	6,050	24	5,532	11,606
2020	6,629	16	6,031	12,676
2021	1,052	2	1,194	2,248
Overall	52,930	298	46,311	99,539
Panel B: Sales KPI Revisions				
2006	2	0	1	3
2007	0	1	0	1
2008	0	0	1	1
2009	1	0	2	3
2010	0	0	0	0
2011	0	0	0	0
2012	208	2	133	343
2013	348	3	229	580
2014	1,546	4	903	2,453
2015	1,099	9	998	2,106
2016	1,194	5	794	1,993
2017	1,645	79	1,233	2,957
2018	1,512	3	1,908	3,423
2019	1,370	13	1,380	2,763
2020	2,680	2	2,844	5,526
2021	398	1	869	1,268
Overall	12,003	122	11,295	23,420

Figure 1. Revisions Relative to Consensus

This figure depicts the coding of positive and negative revisions (described in Table 7) relative to consensus, which is represented by the dashed line. Consensus is calculated as the average forecast value when there is more than one analyst forecast on the prior day for that Firm-Measure (Operational KPI) or Firm-Measure-Region-Product (Sales KPI). If the initial forecast (time t) is above consensus (Panel A), the revision is coded a Jump Below if the revised forecast (time t+1) is below consensus, otherwise it is coded as No Jump. If the initial forecast is below consensus (Panel B), the revision is coded a Jump Above if the revised forecast is above consensus, otherwise it is coded as No Jump. In the case where an initial forecast is exactly equal to consensus, any revised forecast that is not a reiteration will be either a Jump Above or a Jump Below.

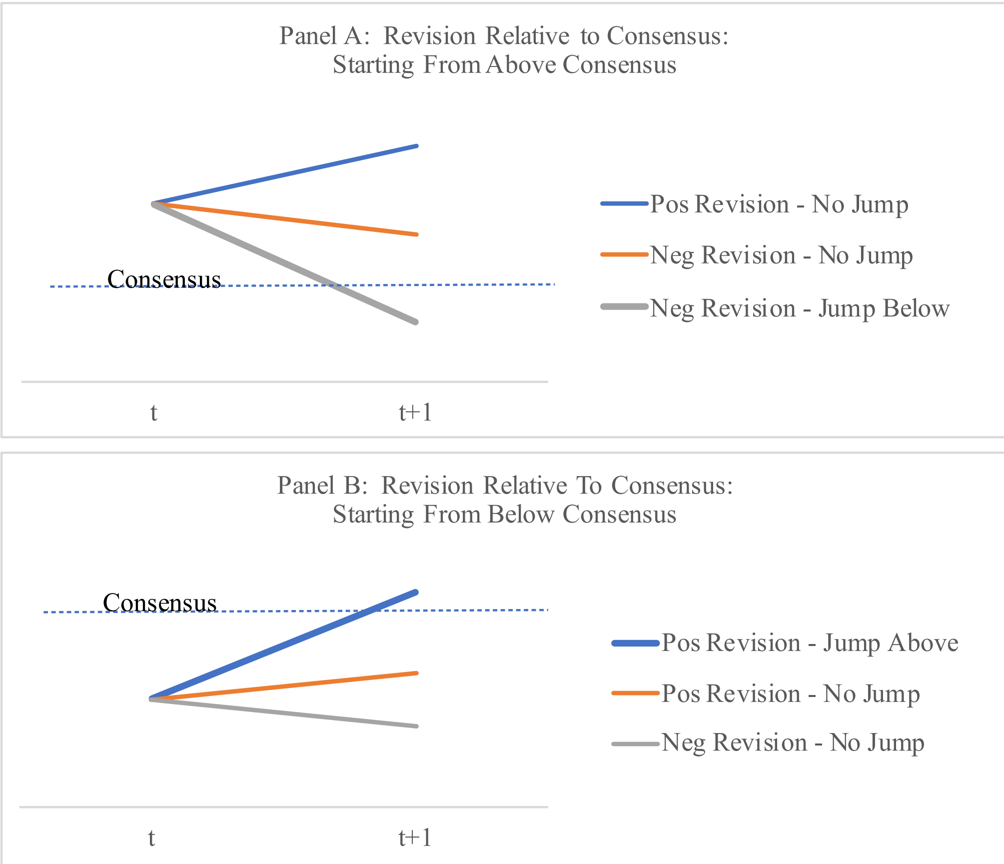

Table 9. Revisions Relative to Consensus by I/B/E/S Sector

This table summarizes the number of Revisions relative to consensus by I/B/E/S Sector in the Operational KPI (Panel A) and Sales KPI (Panel B) datasets. A KPI forecast is coded as a revision as described in Table 7. Revisions are coded as Jump Below, No Jump, or Jump Above as defined in Figure 1.

	Jump Below	*No Jump*	*Jump Above*	*Total*
Panel A: Operational KPI Revisions				
Airlines	707	1,829	550	3,086
All	68	380	40	488
Automobiles	1	5	0	6
Banking and Finance	479	1,338	446	2,263
Energy	13,765	49,478	11,410	74,653
Hotels & Entertainment	40	245	48	333
Insurance	1,532	5,002	1,046	7,580
Media	125	401	147	673
Mining	80	511	68	659
Pharmaceuticals	0	0	0	0
Real Estate	449	1,838	483	2,770
Retail	763	3,659	616	5,038
Technology	216	766	206	1,188
Telecom	74	569	105	748
Transportation	18	26	10	54
Overall	18,317	66,047	15,175	99,539
Panel B: Sales KPI Revisions				
Hotels & Entertainment	8	14	5	27
Pharmaceuticals	1,057	5,282	1,010	7,349
Retail	4,227	7,860	3,868	15,955
Telecom	9	53	27	89
Overall	5,301	13,209	4,910	23,420

Table 10. Revisions with CARs, Recommendation Changes, or EPS Revisions

This table presents the number of forecast revisions with CARs, recommendation changes, or EPS revisions by I/B/E/S Sector in the Operational KPI (Panel A) and Sales KPI (Panel B) datasets. A forecast is coded as a Revision as in Table 3. Cumulative Abnormal Return (CAR) is defined as the stock return in excess of Fama-French 3-factor plus momentum benchmark returns, calculated using a two-step linear model over the three-day window (-1, +1) surrounding the forecast announcement date. CARs were calculated using the Eventus program via WRDS, with non-trading days converted to trading days using the "autodate" specification. CARs were matched to forecasts on PERMNO which were linked to I/B/E/S tickers using the WRDS CRSPLINK file through December 31, 2020, per Singapore Management University's subscription terms. Recommendation changes and EPS revisions were taken from I/B/E/S files RECDDAT and DET_EPS, respectively, both of which had last observation dates of May 20, 2021.

			For Revisions w/ CAR	
	N Revisions	*N Revisions w/ CAR*	*N w/ REC Change*	*N w/ EPS Revision*
	Panel A: Operational KPIs			
Airlines	3,086	2,861	135	2,097
All	488	450	23	340
Automobiles	6	4	0	3
Banking and Finance	2,263	2,151	29	1,237
Energy	74,653	71,688	1,725	47,083
Hotels & Entertainment	333	280	13	192
Insurance	7,580	7,030	167	4,973
Media	673	556	10	352
Mining	659	517	21	207
Pharmaceuticals	0	0	0	0
Real Estate	2,770	2,678	109	1,639
Retail	5,038	4,664	141	2,689
Technology	1,188	1,090	21	571
Telecom	748	653	20	393
Transportation	54	49	3	38
Overall	99,539	94,671	2,417	61,814
	Panel B: Sales KPIs			
Hotels & Entertainment	27	24	0	4
Pharmaceuticals	7,349	5,866	98	1,885
Retail	15,955	14,596	263	3,285
Telecom	89	83	0	37
Overall	23,420	20,569	361	5,211

Table 11. Stock-Price Reaction of Operational KPI Revisions

This table presents regression results for Operational KPI forecast revisions. The dependent variable is CAR as defined in Table 10. *KPIrev_signed* takes a value of 1 for positive revisions, 0 for reiterates, and -1 for negative revisions as defined in Table 7. *RECrev_signed* and *EPSrev_signed* are calculated similarly for recommendation changes and EPS revisions, respectively. *RECrev_flag* and *EPSrev_flag* are dummy variables with the value of 1 for any non-missing value of *RECrev_signed* and *EPSrev_signed*, respectively. *RECrev_signed* and *EPSrev_signed* are non missing when there is a recommendation revision or an EPS forecast revision on the same day as the KPI forecast revision. The interaction variables *kpirev_x_rec* and *kpirev_x_eps* are calculated as the product of *KPIrev_signed* and the respective dummy (_flag) variables. *con_nanalyst* is the number of analysts with forecasts included in the prior day consensus (see Figure 1) for each Firm-Analyst-Measure. *con_std1dayb4* is the standard deviation of the forecasts included in the prior day consensus. Coefficients are multiplied by 100 and presented in basis points (bps). Robust *t*-statistics are in parentheses based on standard errors clustered by announcement date. Analyst and firm fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
KPIrev_signed	0.247***	0.244***	0.241***	0.238***	0.239***	0.237***	0.189***	0.193***	0.156**	0.153**	0.184***	0.189***	0.150**	0.148**
	(5.80)	(5.74)	(5.72)	(5.66)	(5.79)	(5.75)	(4.59)	(4.63)	(2.35)	(2.23)	(4.51)	(4.56)	(2.27)	(2.17)
RECrev_signed			2.376***	2.322***							2.335***	2.288***		
			(4.30)	(4.17)							(4.25)	(4.14)		
RECrev_flag					-0.416	-0.392							-0.415	-0.392
					(-0.92)	(-0.84)							(-0.92)	(-0.84)
kpirev_x_rec					0.298	0.264							0.292	0.258
					(0.91)	(0.76)							(0.89)	(0.74)
EPSrev_signed							0.364***	0.322***			0.354***	0.314***		
							(4.17)	(3.69)			(4.06)	(3.59)		
EPSrev_flag									0.046	0.069			0.048	0.071
									(0.33)	(0.49)			(0.34)	(0.50)
kpirev_x_eps									0.139*	0.139*			0.137*	0.137
									(1.71)	(1.66)			(1.68)	(1.64)
con_nanalyst		-0.021		-0.020		-0.021		-0.021		-0.022		-0.020		-0.022
		(-1.44)		(-1.39)		(-1.45)		(-1.42)		(-1.49)		(-1.36)		(-1.50)
con_std1dayb4		0.000		0.000		0.000		-0.000		-0.000		-0.000		0.000
		(0.17)		(0.18)		(0.18)		(-0.72)		(-0.00)		(-0.68)		(0.01)
F.E. (Analyst, Firm)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.053	0.052	0.056	0.055	0.054	0.052	0.055	0.054	0.054	0.052	0.057	0.056	0.054	0.053
Observations	94,364	89,035	94,364	89,035	94,364	89,035	94,364	89,035	94,364	89,035	94,364	89,035	94,364	89,035

Table 12. Stock-Price Reaction of Sales KPI Revisions

This table presents regression results for Sales KPI forecast revisions. The dependent variable is CAR as defined in Table 10. *SALESrev_signed* takes a value of 1 for positive revisions, 0 for reiterates, and -1 for negative revisions as defined in Table 7. *RECrev_signed* and *EPSrev_signed* are calculated similarly for recommendation changes and EPS revisions, respectively. *RECrev_flag* and *EPSrev_flag* are dummy variables with the value of 1 for any non-missing value of *RECrev_signed* and *EPSrev_signed*, respectively. The interaction variables *SALESrev_x_rec* and *SALESrec_x_eps* are calculated as the product of *SALESrev_signed* and the respective dummy (_flag) variables. *con_nanalyst* is the number of analysts with forecasts included in the prior day consensus (see Figure 1) for each Firm-Analyst-Measure-Region-Product. *con_std1dayb4* is defined as in Table 10. Coefficients are multiplied by 100 and presented in basis points (bps). Robust *t*-statistics are in parentheses with standard errors clustered by announcement date. Analyst and firm fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
SALESrev_signed	0.851***	0.877***	0.825***	0.851***	0.809***	0.836***	0.756***	0.784***	0.848***	0.890***	0.735***	0.763***	0.827***	0.869***
	(9.79)	(9.81)	(9.54)	(9.57)	(9.25)	(9.29)	(9.09)	(9.14)	(9.21)	(9.29)	(8.89)	(8.95)	(8.98)	(9.07)
RECrev_signed			3.956***	3.958***							3.881***	3.887***		
			(6.24)	(6.23)							(6.14)	(6.15)		
RECrev_flag					-0.648	-0.805							-0.762	-0.899
					(-0.90)	(-1.14)							(-1.06)	(-1.27)
SALESrev_x_rec					2.494***	2.423***							2.529***	2.476***
					(3.83)	(3.73)							(3.84)	(3.77)
EPSrev_signed							0.693***	0.660***			0.659***	0.626***		
							(3.51)	(3.39)			(3.35)	(3.23)		
EPSrev_flag									0.410*	0.330			0.429*	0.350
									(1.76)	(1.42)			(1.83)	(1.50)
SALESrev_x_eps									-0.010	-0.070			-0.094	-0.155
									(-0.06)	(-0.40)			(-0.53)	(-0.87)
con_nanalyst		-0.004		-0.002		-0.004		-0.006		-0.004		-0.003		-0.004
		(-0.23)		(-0.09)		(-0.23)		(-0.32)		(-0.24)		(-0.18)		(-0.23)
con_std1dayb4		0.000		-0.000		-0.000		0.000		0.000		-0.000		0.000
		(0.02)		(-0.05)		(-0.00)		(0.07)		(0.05)		(-0.00)		(0.02)
F.E. (Analyst, Firm)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.111	0.108	0.117	0.114	0.113	0.111	0.113	0.110	0.111	0.108	0.119	0.116	0.114	0.111
Observations	20,474	19,076	20,474	19,076	20,474	19,076	20,474	19,076	20,474	19,076	20,474	19,076	20,474	19,076

Table 13. Stock-Price Reaction of Operational KPI Revisions Relative To Consensus

This table presents regression results for a measure of Operational KPI forecast revisions relative to consensus. The dependent variable is CAR as defined in Table 10. Following Figure 1, *KPIrevJump_signed* is coded as 1 if Jump Above, 0 if No Jump, and -1 if Jump Below. The interaction variables *KPIrevJump_x_rec* and *KPIrevJump_x_eps* are equal to the product of *KPIrevJump_signed* and the respective dummy (_flag) variables. All other variables are as described in Table 11. Coefficients are multiplied by 100 and presented in basis points (bps). Robust *t*-statistics are in parentheses with standard errors clustered by announcement date. Analyst and firm fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
KPIrevJump_signed	0.388***	0.386***	0.381***	0.379***	0.383***	0.381***	0.316***	0.322***	0.330***	0.320***	0.311***	0.317***	0.326***	0.316***
	(6.39)	(6.35)	(6.33)	(6.29)	(6.30)	(6.26)	(5.24)	(5.35)	(3.03)	(2.95)	(5.19)	(5.29)	(2.99)	(2.91)
RECrev_signed			2.388***	2.330***							2.341***	2.292***		
			(4.31)	(4.18)							(4.26)	(4.14)		
RECrev_flag					-0.448	-0.417							-0.448	-0.418
					(-0.97)	(-0.87)							(-0.97)	(-0.88)
KPIrevJump_x_rec					0.188	0.188							0.185	0.184
					(0.51)	(0.52)							(0.51)	(0.51)
EPSrev_signed							0.379***	0.335***			0.368***	0.326***		
							(4.32)	(3.84)			(4.21)	(3.74)		
EPSrev_flag									0.037	0.061			0.0383	0.062
									(0.27)	(0.44)			(0.28)	(0.44)
KPIrevJump_x_eps									0.088	0.100			0.0860	0.098
									(0.69)	(0.78)			(0.68)	(0.77)
con_nanalyst		-0.021		-0.020		-0.021		-0.021		-0.022		-0.020		-0.022
		(-1.45)		(-1.39)		(-1.46)		(-1.42)		(-1.49)		(-1.37)		(-1.50)
con_std1dayb4		0.000		0.000		0.000		-0.000		0.000		-0.000		0.000
		(0.89)		(0.88)		(0.89)		(-0.22)		(0.86)		(-0.20)		(0.86)
F.E. (Analyst, Firm)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.053	0.052	0.056	0.054	0.053	0.052	0.055	0.054	0.053	0.052	0.057	0.056	0.053	0.052
Observations	94,364	89,035	94,364	89,035	94,364	89,035	94,364	89,035	94,364	89,035	94,364	89,035	94,364	89,035

Table 14. Stock-Price Reaction of Sales KPI Revisions Relative to Consensus

This table presents regression results for a measure of Sales KPI forecast revisions relative to consensus. The dependent variable is CAR as defined in Table 10. Following Figure 1, *SALESrevJump_signed* is coded as 1 if Jump Above, 0 if No Jump, and -1 if Jump Below. The interaction variables *SALESrevJump_x_rec* and *SalesrevJump_x_eps* are equal to the product of *SALESrevJump_signed* and the respective dummy (_flag) variables. All other variables are as described in Table 11. Coefficients are multiplied by 100 and presented in basis points (bps). Robust *t*-statistics are in parentheses with standard errors clustered by announcement date. Analyst and firm fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
SALESrev_jump	1.116***	1.110***	1.089***	1.083***	1.073***	1.068***	0.981***	0.980***	1.162***	1.155***	0.961***	0.960***	1.140***	1.133***
	(9.45)	(9.44)	(9.29)	(9.28)	(9.09)	(9.09)	(8.78)	(8.81)	(9.86)	(9.83)	(8.69)	(8.72)	(9.72)	(9.69)
RECrev_signed			4.080***	4.078***							3.974***	3.978***		
			(6.43)	(6.41)							(6.28)	(6.30)		
RECrev_flag					-0.362	-0.534							-0.466	-0.620
					(-0.50)	(-0.76)							(-0.65)	(-0.89)
SALESrev_jump_x_rec					2.487**	2.454**							2.557***	2.526***
					(2.57)	(2.57)							(2.60)	(2.60)
EPSrev_signed							0.813***	0.784***			0.772***	0.743***		
							(4.13)	(4.04)			(3.95)	(3.86)		
EPSrev_flag									0.410*	0.337			0.411*	0.342
									(1.75)	(1.44)			(1.75)	(1.46)
SALESrev_jump_x_eps									-0.219	-0.207			-0.304	-0.291
									(-0.86)	(-0.81)			(-1.16)	(-1.11)
con_nanalyst		-0.008		-0.005		-0.008		-0.009		-0.008		-0.007		-0.008
		(-0.41)		(-0.27)		(-0.41)		(-0.49)		(-0.41)		(-0.35)		(-0.40)
con_std1dayb4		0.000		0.000		0.000		0.000		0.000		0.000		0.000
		(0.15)		(0.06)		(0.12)		(0.20)		(0.19)		(0.11)		(0.18)
F.E. (Analyst, Firm)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.107	0.104	0.114	0.111	0.108	0.106	0.111	0.108	0.108	0.105	0.117	0.114	0.109	0.106
Observations	20,474	19,076	20,474	19,076	20,474	19,076	20,474	19,076	20,474	19,076	20,474	19,076	20,474	19,076

Figure 2. Stock-Price Reaction to Different Measures of KPI Revision

This figure shows the KPI regression coefficients with and without controls from Tables 11-14 under four different combination of models: KPI Alone (Models 1-2), KPI Controlling For Recommendation Changes (Models 3-4), KPI Controlling for EPS Revisions (Models 7-8), and KPI Controlling For Both Recommendation Changes and EPS Revisions (Models 11-12). Panels A and B show coefficients for the *KPIrev_signed* and *SALESrev_signed* variables for Operational and Sales KPIs from Tables 11 and 12, respectively. Panels C and D show coefficients for the *KPIrevJump_signed* and *SALESrevJump*_signed variables for Operational and Sales KPIs from Tables 13 and 14, respectively.

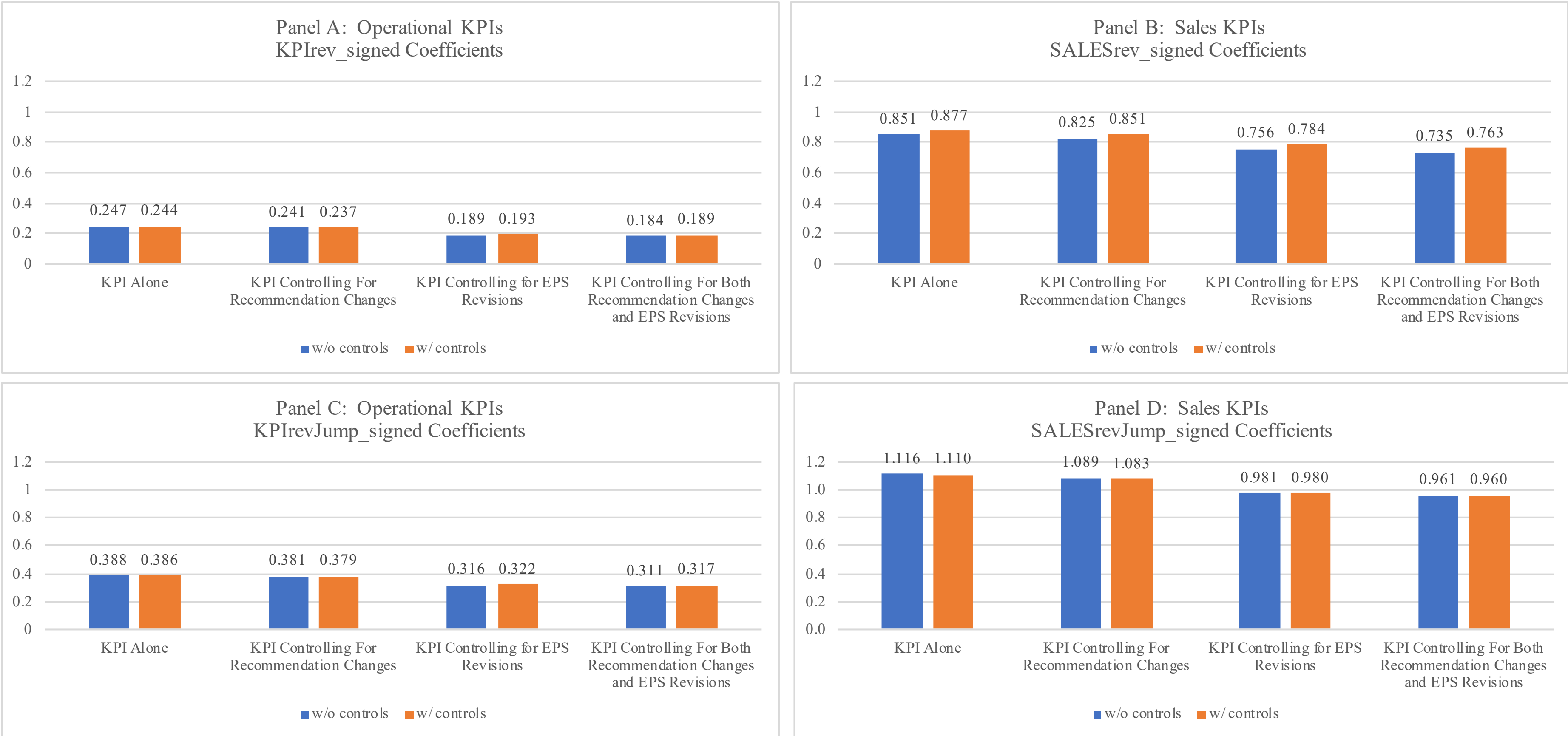

Table 15. Stock-Price Reaction of Revisions to Revenue-Related KPIs

This table presents regression results for Operational KPI forecast revisions of revenue-focused measures. The dependent variable is CAR as defined in Table 10. *KPIrev_signed* is as defined in Table 11. *revenue_flag* is coded 1 if KPIflag=1, otherwise 0, for each forecast measure (see Appendix). The interaction variable *kpirev_x_revenue* is the product of *KPIrev_signed* and *revenue_flag*. Control variables are defined as in Table 11. Coefficients are multiplied by 100 and presented in basis points (bps). Robust *t*-statistics are in parentheses with standard errors clustered by announcement date. Analyst and sector fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
KPIrev_signed	0.314***	0.377***
	(4.21)	(4.91)
revenue_flag	0.201*	0.171
	(1.72)	(1.44)
kpirev_x_revenue	-0.0383	-0.102
	(-0.43)	(-1.14)
con_nanalyst		-0.000
		(-0.01)
con_std1dayb4		0.000
		(0.59)
F.E. (Analyst, Sector)	Yes	Yes
Adj. R-squared	0.017	0.018
Observations	94,501	89,126

Table 16. Stock-Price Reaction of Sales KPI Revisions for I/B/E/S Retail Sector

This table presents regression results for Sales KPI forecast revisions. The dependent variable is CAR as defined in Table 10. *SALESrev_signed* is defined as in Table 12. *Retail_flag* is coded as 1 if the I/B/E/S sector is Retail and 0 otherwise. The interaction variable *SALESrev_x_retail* is calculated as the product of *SALESrev_signed* and *retail_flag*. Control variables are defined as in Table 12. Coefficients are multiplied by 100 and presented in basis points (bps). Robust *t*-statistics are in parentheses with standard errors clustered by announcement date. Analyst fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
SALESrev_signed	0.203**	0.263**
	(1.96)	(2.42)
retail_flag	-2.036	-3.017*
	(-1.31)	(-1.88)
SALESrev_x_retail	1.007***	0.940***
	(6.83)	(6.25)
con_nanalyst		0.000
		(-0.03)
con_std1dayb4		0.000
		(1.34)
F.E. (Analyst)	Yes	Yes
Adj. R-squared	0.049	0.447
Observations	20,512	19,100

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Appendix: Description of Measures by I/B/E/S Sector

This Appendix presents descriptive information by I/B/E/S Sector for Operational (Panel A) and Sales (Panel B) KPI measures. Detail_Start refers to the month and year when KPI forecasts for that measure were first published. Level is the I/B/E/S subscription level which enables access to the Measure. KPIsign is coded 1 if larger values are positive (e.g., revenues) and -1 if larger values are negative (e.g., expenses). KPIflag is coded 1 for KPIs included in the samples used for this paper, otherwise 0. Source data taken from "Thomson Reuters IBES – Estimates History Start Dates By Region And Measure (2019)."

Measure	*Description*	*Detail_Start*	*Level*	*KPIsign*	*KPIflag*
	Panel A: Operational KPIs				
Airline					
ASK	Available Seat Kilometers	Apr-2013	Level III KPI	1	1
ASM	Available Seat Miles	Apr-2013	Level III KPI	1	1
CFC	Completion Factor	Jul-2016	Level III KPI	1	1
CPA	Cost per Available Seat Miles	Apr-2013	Level III KPI	-1	1
OEA	Cost per Available Seat Kilometers	Apr-2013	Level III KPI	-1	1
PLF	Passenger Load Factor	Apr-2013	Level III KPI	1	1
PRA	Revenue per Available Seat Kilometers	Apr-2013	Level III KPI	1	1
PRK	Revenue per Available Seat Miles	Apr-2013	Level III KPI	1	1
RPK	Revenue Passenger Kilometers	Apr-2013	Level III KPI	1	1
RPM	Revenue Passenger Miles	Apr-2013	Level III KPI	1	1
RPP	Revenue per RPM	Apr-2013	Level III KPI	1	1
RTR	Revenue per RPK	Apr-2013	Level III KPI	1	1
All					
AMT	Amortization	Jul-2013	Level III	-1	0
BPS	Book Value per Share	Dec-1996	Level III	1	0
CCE	Cash & Cash Equivalents	Jul-2016	Level III	1	0
CFF	Cash Flow from Financing	Jul-2013	Level III	1	0
CFI	Cash Flow from Investing	Jul-2013	Level III	1	0
CFO	Cash Flow from Operations	Jul-2013	Level III	1	0
CGS	Cost of goods sold	Aug-2013	Level III	-1	0
CPS	Cash Flow per Share	Feb-1990	Level II	1	0
CPX	Capital Expenditure	Jul-2006	Level III	-1	0
CRA	Current Assets	Jul-2016	Level III	1	0
CRL	Current Liabilities	Jul-2016	Level III	-1	0
CRT	Compensation Ratio	Jun-2013	Level III	-1	1
CSH	Earnings per Share - Cash	Jul-2002	Level III	1	0
DFR	Current Deferred Revenue	Jul-2016	Level III	1	0
DPA	Depreciation and Amortization	Jul-2013	Level III	-1	0
DPR	Depreciation	Jul-2013	Level III	-1	0
DPS	Dividend per Share	Dec-1993	Level II	1	0
EBA	Earnings before Interest, Tax and Amortization	Jul-2013	Level III	1	0
EBG	Earnings per Share - Before Goodwill	Jul-1994	Level II	1	0
EBI	EBIT	May-1999	Level III	1	0
EBP	Earnings before Interest, Tax and Amortization Reported (EBITDA Reported)	Jun-2013	Level III	1	0
EBR	Earnings before Interest, Tax, Amortization and Rental (EBITDAR)	Jun-2013	Level III	1	0
EBS	EBITDA per Share	Aug-2002	Level III	1	0
EBT	EBITDA	Dec-1998	Level III	1	0
ENT	Enterprise Value	Jul-2006	Level III	1	0
EPS	Earnings per Share	Feb-1982	Level I	1	0
EPX	Earnings per Share - Alternate	Jul-2002	Level III	1	0
FCD	Franking Credits	Jan-2014	Level III	1	0
FCF	Free Cash Flow per Share	Jul-2007	Level III	1	0
FRC	Free Cash Flow	Jul-2013	Level III	1	0
GAE	General & Admin Expense	Aug-2014	Level III	-1	0
GCX	Growth Capex	Jul-2015	Level III	-1	0
GPS	Earnings per Share - Fully Reported	Aug-2003	Level III	1	0
GRI	Gross Income	Jul-2013	Level III	1	0
GRM	Gross Margin	Jul-2006	Level III	1	0
GWL	Goodwill	Jul-2013	Level III	1	0
INE	Interest Expense	Oct-2012	Level III	-1	0
INV	Inventory	Dec-2013	Level III	1	0
ITX	Income Taxes Paid	Jul-2013	Level III	-1	0

Panel A: Operational KPIs (cont.)

Measure	*Description*	*Detail_Start*	*Level*	*KPIsign*	*KPIflag*
All (cont.)					
LTG	Long Term Growth Rate (%)	Jan-1976	Level I	1	0
LTR	Long-Term Deferred Revenue	Oct - 2017	Level III	1	0
NAV	Net Asset Value	May-1999	Level III	1	0
NDT	Net Debt	Jul-2000	Level III	-1	0
NER	Reported Net Income	Jul-2008	Level III	1	0
NET	Net Income	Nov-1994	Level III	1	0
NIT	Net Investment Income	Jul-2013	Level III	1	0
NPS	NAV per Share	Jun-2013	Level III	1	0
NSO	Number of Shares Outstanding	Jul-2013	Level III	-1	0
NWC	Net Working Capital	Jul-2013	Level III	1	0
OPE	Operating Expense	Sep-2012	Level III	-1	0
OPR	Operating Profit	Jul-1997	Level III	1	0
OSG	Organic Sales Growth	Dec-2013	Level III	1	0
PRE	Pre-tax Profit	Jul-1994	Level II	1	0
PRR	Reported Pre-Tax Profit	Jul-2008	Level III	1	0
PSR	Price/Sales Ratio	Jul-2013	Level III	1	0
PTG	Price Target	Mar-1999	Level III	1	0
RDE	R&D Expense	Jun-2013	Level III	-1	0
REC	Recommendation	Nov-1993	Level II	1	0
RIC	Return on Invested Capital	Jul-2013	Level III	1	0
ROA	Return on Assets (%)	Aug-1999	Level III	1	0
ROC	Return on Capital	Jul-2013	Level III	1	0
ROE	Return on Equity (%)	May-1999	Level III	1	0
SBC	Stock Based Compensation	Jun-2013	Level III	-1	0
SGE	SG&A Expense	Jun-2013	Level III	-1	0
SHE	Shareholders' Equity	Oct-2012	Level III	1	0
SMK	Selling & Marketing Expense	Aug-2014	Level III	-1	0
TAS	Total Assets	Sep-2012	Level III	1	0
TBV	Tangible Book Value per Share	Jul-2008	Level III	1	0
TCE	Total Compensation Expense	Jun-2013	Level III	-1	0
TDT	Total Debt	Jul-2016	Level III KPI	-1	0
TDV	Total Dividends	Jul-2013	Level III KPI	1	0
TXP	Tax Provision	Jul-2013	Level III KPI	-1	0
TXR	Tax Rate	Jul-2013	Level III KPI	-1	0
Automobiles					
ASP	Average Selling Price	Oct-2017	Level III KPI	1	1
MOS	Motorcycle Shipments	Oct-2017	Level III KPI	1	1
Banking and Finance					
AUM	Assets Under Management	Dec-2012	Level III KPI	1	1
BLB	Billed Business	Dec-2012	Level III KPI	1	1
CDT	Customer Deposits Under Total Deposits	Dec-2012	Level III KPI	1	0
CTO	Core Tier 1 Capital	Oct-2012	Level III KPI	1	0
DSF	Discount Fees	Dec-2012	Level III KPI	-1	0
EFR	Efficiency Ratio (%)	Sep-2012	Level III KPI	1	0
FCI	Fees & Commission Income	Oct-2012	Level III KPI	1	0
IBV	Intangible Book Value	Dec-2012	Level III KPI	1	0
LLP	Loan Loss Provision	Sep-2012	Level III KPI	-1	0
LNS	Loans	Sep-2012	Level III KPI	1	0
NAL	Net Charge-Offs to Average Loans	Oct-2012	Level III KPI	-1	0
NGL	Net Gains or Losses	Dec-2012	Level III KPI	1	0
NIE	Non-Interest Expense	Oct-2012	Level III KPI	-1	0
NII	Net Interest Income	Sep-2012	Level III KPI	1	0
NIM	Net Interest Margin (%)	Sep-2012	Level III KPI	1	0
NIR	Total Non-Interest Revenue	Sep-2012	Level III KPI	1	0
NIS	Net Interest Spread (%)	Dec-2012	Level III KPI	1	0
NNM	Net New Money/Assets	Dec-2012	Level III KPI	1	1

Panel A: Operational KPIs (cont.)

Measure	*Description*	*Detail_Start*	*Level*	*KPIsign*	*KPIflag*
Banking and Finance (cont.)					
NPA	Non-Performing Assets	Oct-2012	Level III KPI	-1	0
NPL	Non-Performing Loans	Oct-2012	Level III KPI	-1	0
NRI	Non-Recurring Items	Dec-2012	Level III KPI	-1	0
ORE	Other Real Estate Owned Expenses	Dec-2012	Level III KPI	-1	0
RNA	Return on Net Operating Assets (%)	Dec-2012	Level III KPI	1	0
RWA	Risk Weighted Assets	Sep-2012	Level III KPI	-1	0
SID	Securities in Issue Under Total Deposits	Dec-2012	Level III KPI	1	0
TCO	Tier 1 Capital Ratio (%)	Oct-2012	Level III KPI	1	0
TDI	Trading Income	Oct-2012	Level III KPI	1	0
TDO	Total Deposits	Sep-2012	Level III KPI	1	0
TIN	Total Income	Oct-2012	Level III KPI	1	0
TNB	Tangible Book Value (Non per Share)	Dec-2012	Level III KPI	1	0
TRI	Total Revenue Net of Interest Expense	Dec-2012	Level III KPI	1	0
Energy					
CNC	Chemicals Income	May-2012	Level III KPI	1	0
DFF	Distributable Cash Flow Aggregate	Apr-2013	Level III KPI	1	0
DWI	Downstream Income	Dec-2012	Level III KPI	1	0
EBX	Earnings before Interest, Tax, Amortization and Exploration (EBITDAX)	May-2012	Level III KPI	1	0
EXP	Exploration Expense	May-2012	Level III KPI	-1	1
GPD	Gas Production per Day	Dec-2012	Level III KPI	1	1
LOE	Lease Operating Expense	Dec-2013	Level III KPI	-1	0
MCX	Maintenance Capex	Apr-2013	Level III KPI	-1	0
MNC	Marketing Income	May-2012	Level III KPI	1	0
NPP	Natural Gas Liquids Production per Day	Dec-2012	Level III KPI	1	1
OPD	Oil Production per Day	Dec-2012	Level III KPI	1	1
OPU	OPEX Per Unit	Aug-2014	Level III KPI	-1	1
PEX	Production Expense	Dec-2013	Level III KPI	-1	0
PTX	Production Tax	Apr-2013	Level III KPI	-1	0
PVR	1P Proved Reserves	Aug-2014	Level III KPI	1	1
RNC	Refining Income	May-2012	Level III KPI	1	0
RPG	Realized Price - Gas	Dec-2013	Level III KPI	1	1
RPO	Realized Price - Oil	Dec-2013	Level III KPI	1	1
RZP	Realized Price (BOE)	Jul-2013	Level III KPI	1	1
TPC	Total Production Total	Aug-2014	Level III KPI	1	1
TPD	Total Production per Day (in BOE)	Dec-2012	Level III KPI	1	1
TPG	Total Production Gas	Aug-2014	Level III KPI	1	1
TPI	Throughput Info	Dec-2012	Level III KPI	1	1
TPN	Total Production NGL	Aug-2014	Level III KPI	1	1
TPO	Total Production Oil	Aug-2014	Level III KPI	1	1
TPP	Total Production per Day	Dec-2012	Level III KPI	1	1
UPI	Upstream Income	Dec-2012	Level III KPI	1	0
Hotels & Entertainment					
ATD	Attendance	Oct-2017	Level III KPI	1	1
GWN	Gross Win	Oct-2017	Level III KPI	1	1
REE	Restaurant Expense	Jan - 2018	Level III KPI	-1	1
Insurance					
APE	Annual Premium Earned	Dec-2012	Level III KPI	1	1
BEV	Book Value on Embedded Value Basis	Dec-2012	Level III KPI	1	0
BKV	Book Value on GAAP Basis	Dec-2012	Level III KPI	1	0
CLR	Catastrophic Loss Ratio (%)	Dec-2012	Level III KPI	-1	1
CMR	Claims Ratio (%)	Dec-2012	Level III KPI	-1	1
COR	Combined Ratio (%)	Dec-2012	Level III KPI	-1	1
CSL	Consolidated Loss Ratio (%)	Dec-2012	Level III KPI	-1	1
EBV	Embedded Value	Dec-2012	Level III KPI	1	0
EVO	Embedded Value Operating Profits (%)	Dec-2012	Level III KPI	1	0
EXR	Expense Ratio (%)	Dec-2012	Level III KPI	-1	0

Panel A: Operational KPIs (cont.)					
Measure	*Description*	*Detail_Start*	*Level*	*KPIsign*	*KPIflag*
Insurance (cont.)					
GEP	Gross Earned Premiums	Dec-2012	Level III KPI	1	1
GPW	Gross Premium Written	Dec-2012	Level III KPI	1	1
MLR	Medical Loss Ratio (%)	Dec-2012	Level III KPI	-1	1
NEV	Net Income on Embedded Value Basis	Dec-2012	Level III KPI	1	0
NPE	Net Premiums Earned	Dec-2012	Level III KPI	1	1
NPW	Net Premiums Written	Dec-2012	Level III KPI	1	1
RZG	Realized Gain or Losses	Dec-2012	Level III KPI	1	0
SLM	Solvency Margin	Oct-2017	Level III KPI	1	0
VNB	Value of New Business	Dec-2012	Level III KPI	1	1
Media					
ABP	Average Booking Per User	Nov-2017	Level III KPI	1	1
ARV	Advertisement Revenue	Oct-2017	Level III KPI	1	1
CPK	Cost Per Click	Oct-2017	Level III KPI	-1	1
CPM	Cost Per Mille	Oct-2017	Level III KPI	-1	1
DAR	Daily Active Users	Oct-2017	Level III KPI	1	1
GMV	Gross Merchandised Value	Oct-2017	Level III KPI	1	1
MAU	Monthly Active Users	Oct-2017	Level III KPI	1	1
MUP	Monthly Unique Payers	Oct-2017	Level III KPI	1	1
MUU	Monthly Unique Users	Oct-2017	Level III KPI	1	1
NMV	Net Merchandised Value	Dec-2017	Level III KPI	1	1
Mining					
ACG	All In Production Cost (AISC) - Gold	Jul-2016	Level III KPI	-1	1
ACS	All In Production Cost (AISC) - Silver	Jul-2016	Level III KPI	-1	1
APS	Average Price (Per Metric Tonne) - Steel	Jul-2016	Level III KPI	-1	1
CCC	Mining Cash Cost (oz) – Copper	Jul-2016	Level III KPI	-1	1
LMP	Lead Metal Processing Production	Oct-2017	Level III KPI	1	1
MCC	Mining Cash Cost (oz) - Total	Aug-2014	Level III KPI	-1	1
MCG	Mining Cash Cost (oz) - Gold	Aug-2014	Level III KPI	-1	1
MCP	Mining Cash Cost (oz) - Platinum	Sep-2014	Level III KPI	-1	1
MCS	Mining Cash Cost (oz) - Silver	Aug-2014	Level III KPI	-1	1
MPG	Mining Production (oz) - Gold	Aug-2014	Level III KPI	1	1
MPP	Mining Production (oz) - Platinum	Sep-2014	Level III KPI	1	1
MPS	Mining Production (oz) - Silver	Aug-2014	Level III KPI	1	1
RGO	Realized Price - Gold	Jul-2016	Level III KPI	1	1
RPC	Realized Price – Copper	Jul-2016	Level III KPI	1	1
RPS	Realized Price – Silver	Jul-2016	Level III KPI	1	1
TMP	Mining Production (oz) - Total	Aug-2014	Level III KPI	1	1
TOC	Total Production – Copper (Weight)	Jul-2016	Level III KPI	1	1
TSE	Total Silver Equivalent Production (Weight)	Jul-2016	Level III KPI	1	1
USS	Unit Sales – Steel	Jul-2016	Level III KPI	1	1
Pharmaceutical and Healthcare					
MME	Membership Enrollment	Apr-2013	Level III KPI	1	1
NOD	Number of Doctors	Apr-2013	Level III KPI	1	1
Real Estate					
FFO	Funds from Operations per Share	Mar-1990	Level II	1	0
AFF	Analyst Adjusted Funds From Operation	Dec-2012	Level III KPI	1	0
AFO	Adjusted Funds From Operations per Share	Jul-2007	Level III KPI	1	0
BAP	Backlog Average Price	Apr-2013	Level III KPI	1	1
BGV	Backlog Values	Apr-2013	Level III KPI	1	1
BKU	Backlog Units	Apr-2013	Level III KPI	1	1
CTS	Contracted Sales	Dec-2012	Level III KPI	1	1
DAP	Deliveries Average Price	Apr-2013	Level III KPI	1	1
DCF	Distributable Cash Flow Per Unit	Dec-2012	Level III KPI	1	0
DLU	Deliveries (Number of Units)	Apr-2013	Level III KPI	1	1
DLV	Deliveries (Monetary Value)	Apr-2013	Level III KPI	1	1
DVC	Development Costs	Dec-2012	Level III KPI	-1	1
FOP	Company Defined Fund from Operations	Dec-2012	Level III KPI	1	0
FSV	Financial Services Sales	Apr-2013	Level III KPI	1	0

Panel A: Operational KPIs (cont.)					
Measure	*Description*	*Detail_Start*	*Level*	*KPIsign*	*KPIflag*
Real Estate (cont.)					
HSL	Home Sales	Apr-2013	Level III KPI	1	1
LCH	Launches	Apr-2013	Level III KPI	1	1
LLS	Land/Lot sales	Apr-2013	Level III KPI	1	1
NCR	Net Operating Income Margin (%)	Dec-2012	Level III KPI	1	0
NFO	NAREIT-Defined Funds From Operation per Share	Dec-2012	Level III KPI	1	0
NNV	Non-Periodic Net Asset Value	Dec-2012	Level III KPI	1	0
NOA	New Orders Average Price	Apr-2013	Level III KPI	1	1
NOI	Net Operating Income	Dec-2012	Level III KPI	1	0
NOU	New Orders Unit	Apr-2013	Level III KPI	1	1
NOV	New Orders Value	Apr-2013	Level III KPI	1	1
NPN	Non-Periodic Net Assets Value per Share	Dec-2012	Level III KPI	1	0
OCR	Occupancy Rate (%)	Dec-2012	Level III KPI	1	1
PMN	Premium to Net Asset Value (%)	Dec-2012	Level III KPI	1	0
PRN	Price to Net Asset Value (%)	Dec-2012	Level III KPI	1	0
RSM	Rent per Square Foot	Dec-2012	Level III KPI	1	1
VCR	Vacancy Rate (%)	Dec-2012	Level III KPI	-1	1
Retail					
DOS	Department Store Sales	Apr-2013	Level III KPI	1	1
FLF	Franchise & Licensing Fees	Aug-2014	Level III KPI	1	1
FLS	Floor Space	Apr-2013	Level III KPI	1	1
NAS	Net Sales per Average Square Foot	Apr-2013	Level III KPI	1	1
NOO	Number of Stores Opened (by Total)	Apr-2013	Level III KPI	1	1
NOS	Number of Stores (by Total)	Apr-2013	Level III KPI	1	1
NSC	Number of Stores Closed/Relocated	Apr-2013	Level III KPI	-1	1
POC	Pre-Opening Expenses	Aug-2014	Level III KPI	-1	0
RES	Retail Sales	Apr-2013	Level III KPI	1	1
REX	Rent Expense	Apr-2013	Level III KPI	-1	0
Technology					
BBR	Book to Bill Ratio	Oct-2017	Level III KPI	1	1
BIL	Billings	Oct-2017	Level III KPI	1	1
BKG	Bookings	Oct-2017	Level III KPI	1	1
GPV	Gross Payment Volume	Oct-2017	Level III KPI	1	0
NRV	Net Revenue	Apr-2013	Level III KPI	1	0
TAC	Traffic Acquisition Cost	Apr-2013	Level III KPI	-1	1
TPV	Total Payment Volume	Jan-2018	Level III KPI	1	1
Telecom					
ACL	Access Lines	Aug-2014	Level III KPI	1	1
ARP	Average Revenue Per Unit	Aug-2014	Level III KPI	1	1
CRN	CHURN (%)	Aug-2014	Level III KPI	-1	1
GSA	Gross Subscriber Additions	Sep-2014	Level III KPI	1	1
NSA	Net Subscriber Additions	Aug-2014	Level III KPI	1	1
SAC	Subscriber Acquisition Costs	Aug-2014	Level III KPI	-1	1
SUB	Subscribers	Aug-2014	Level III KPI	1	1
Transportation					
CAK	Cargo Available Tonne Kilometers	Oct-2017	Level III KPI	1	1
CFR	Average Container Freight Rate	Feb-2018	Level III KPI	1	1
CRK	Cargo Revenue Yield Per Tonne Kilometers	Oct-2017	Level III KPI	1	1
RCK	Revenue Cargo Tonne Kilometers	Jan-2018	Level III KPI	1	1
TEU	TEUs Handled	Oct-2017	Level III KPI	1	1
TRL	Total Railcar Loads	Oct-2017	Level III KPI	1	1

Panel B: Sales KPIs					
Measure	*Description*	*Detail_Start*	*Level*	*KPIsign*	*KPIflag*
Business Segment					0
BBI	Business Segment EBIT	Oct-2017	Level III KPI	1	0
BBP	Business Segment EBITDA (Reported)	Jan-2018	Level III KPI	1	0
BBT	Business Segment EBITDA	Jan-2018	Level III KPI	1	0
BSA	Business Segment Net Subscriber Addition	Jan-2018	Level III KPI	1	0
BSL	Business Segment Revenue	Jul-2016	Level III KPI	1	0
Geographic Segment					
GBI	Geographic Segment EBIT	Oct-2017	Level III KPI	1	0
GBP	Geographic Segment EBITDA (Reported)	Jan-2018	Level III KPI	1	0
GBT	Geographic Segment EBITDA	Jan-2018	Level III KPI	1	0
GSL	Geographic Segment Revenue	Jul-2016	Level III KPI	1	0
Hotel and Entertainment					
RAR	Revenue Per Available Room	Jan-2007	Level III KPI	1	1
Pharmaceutical and Healthcare					
SAL	Pharmaceutical Sales	Jan-2005	Level III KPI	1	1
Retail					
SSS	Same Store Sales	Jan-2007	Level III KPI	1	1
Telecom					
GSA	Geographic Segment Net Subscriber Addition	Jan-2018	Level III KPI	1	1