# Industry Expert Analysts and KPI Forecasts*

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Abstract

We explore the mechanism through which analyst industry expertise facilitates analysts' forecasting performance. Utilizing a unique dataset of industry-specific Key Performance Indicator (KPI) estimates issued by equity analysts, our analysis reveals that analysts with relevant pre-analyst industry experience exhibit superior KPI forecasting abilities compared to similar non-industry-expert analysts. This inference is robust to a stringent set of fixed effects and an identification strategy based on brokerage house closure and analyst retirement. The benefit of industry expertise becomes more pronounced in industries with higher uncertainty and technological change. Furthermore, when categorizing KPIs into monetary and volume categories, we find that the benefit of industry expertise is more pronounced with monetary KPIs, especially during periods of unexpected inflation. Capital market tests indicate that industry expert analysts' KPI forecast revisions contain more information than those of non-experts. Path analysis reveals that the positive effect of industry expertise on EPS forecast accuracy documented in Bradley et al. (2017) is partially driven by a KPI forecasting channel. Our study enriches the understanding of a specific type of non-financial disclosure.

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## 1. Introduction

Equity analysts play a pivotal role in financial market developments as they digest the information contained in corporate disclosures and issue their forecasts on future firm performance and stock recommendations, bridging the demand for and supply of information from investors and managers. Even though evidence from the field (Brown et al., 2015), as well as academic research (Bradley et al., 2017a), indicate that industry knowledge is important to sell-side analysts' performance and career development, the question of *how* analysts apply their industry expertise to achieve better earnings forecast accuracy remains unclear. We contend that one mechanism is applying industry expertise to the operational Key-Performance-Indicator (i.e., KPI) metrics. Prior studies indicate that analysts bear significant costs (e.g., time and effort) in interpreting signals that do not match their knowledge structure (Kahneman, 1973; Iselin, 1988; Hirshleifer and Teoh, 2003). Given the industry-specific nature of KPI items (Givoly et al., 2019), it follows that knowledge and experience via working in an industry can lower the costs of untangling industry-specific disclosure, thereby improving analysts' ability to interpret and forecast industry-specific KPIs. Against this backdrop, we posit that the industry experience of sell-side analysts leads to improved KPI forecast accuracy and, consequently, to better EPS forecasts.

Our argument is not without tensions. On the one hand, forecasting multiple items can facilitate analysts' understanding of the interrelationships between a firm's operating, investing, and financing activities (Lundholm and Sloan, 2004). Arguably, a company's strategy, operations, and performance are significantly shaped by the company's peers and, in general, by the industry in which the company operates (PWC, 2007). Hence, operationally-oriented and industry-specific KPI metrics such as *Sales per Store* or *New Customers per Quarter* provide a meaningful representation of the underlying operations of a company, complementing the information contained in the financial statements. In particular, interpreting and forecasting a firm's KPI items can complement the information content of conventional financial disclosure and boost the ability of analysts to develop a comprehensive understanding of a company's expected performance. Due to a close match between their expertise and the nature of KPI items, industry expert analysts can be better equipped to analyze, interpret, and incorporate KPI metrics than non-industry experts. This can position them to develop a more profound understanding of a firm's underlying operations and to improve their forecasts of a firm's overall performance.

On the other hand, forecasting KPI metrics in addition to conventional financial line items adds to the effort requirement for the analyst and increases analysts' task complexity, potentially compromising their forecasting performance. Studies in psychology and social sciences (Kahneman, 1973; Cohen, 1980; Eppler and Mengis, 2004) suggest that limited attention and information overload are major reasons why individuals fail to process information comprehensively. In the analyst literature, findings (Clement, 1999; Harford et al., 2019; Bourveau et al., 2024) indicate that the size of the portfolio of firms covered by an analyst is associated with his degree of limited attention. In a similar vein, a limited attention problem may arise within the same firm when the number of forecasts produced by an analyst increases. Further, given the different nature of financial items and operational KPIs, analysts may face a challenge in switching their analytical approach between the two types of metric forecasting, resulting in inappropriate attention to all tasks at hand and, consequently, less accurate KPI and overall forecasting outputs. A mere-exposure effect or familiarity principle suggests that industry expert analysts may develop a bias in attention allocation to KPI items, rendering them more susceptible to the cognitive limitations discussed above.[1] Thus, it remains an empirical question whether industry expertise benefits analysts in the interpretation, analysis, and forecasting of industry-specific operational KPIs and, in turn, enhances the overall performance of industry expert *vis-à-vis* non-expert analysts.

Our first set of test specifications targets the question of whether analysts' industry expertise enhances their KPI forecast accuracy. We leverage KPI analyst forecasts from FactSet Standard DataFeed

[1] Furthermore, people tend to underweight abstract, statistical, and base-rate information (e.g., Kahneman and Tversky, 1973; Nisbett and Ross, 1980). In the context of financial disclosure information processing, this suggests that analysts that pay less attention to descriptions of operations may be less prone to this bias.

Estimates, which mitigate data limitations compared to other financial analyst data providers (Call et al., 2021; Hand et al., 2022). Additionally, we incorporate analysts' historical career experience from the FactSet People database to construct a measure of industry expertise based on analysts' preanalyst industry experience (Bradley et al., 2017a). We find strong supporting evidence. Specifically, after controlling for analyst-by-quarter, firm, and KPI forecast item fixed effects, we observe that analyst industry expertise is associated with a 27% lower KPI forecast error than non-industry experts. To establish causal inference, we explore an identification strategy based on brokerage house closures (Kelly and Ljungqvist, 2012) and analyst retirement cases (Gokkaya et al., 2023) to generate an exogenous shock to the analyst assignments to companies. We find that upon the exogenous loss of industry expert analysts, KPI forecast accuracy decreases by about 39% relative to control firms. Next, we check whether our results are robust to empirical design variations. Our results remain robust when using alternative metrics to define the industry expertise variable, employing an alternative measure of forecast accuracy; and aggregating the sample at the analyst-firm level, the KPI-firm level, and the firm level.

Furthermore, we conduct additional tests to scrutinize alternative explanations, such as the educational background of analysts, which may influence our results (Jacob et al., 1999). Intuitively, analysts with certain educational backgrounds may be better able to interpret operational and industry-specific information even without first-hand working experience in an industry. To filter out these alternative explanations, we control for the analysts' educational background with variables that capture the type of their educational training and the prestige of the institutions that grant their degrees (Useem and Karabel, 1986; Domhoff, 2002). We find that analysts' educational prestige or credentials do not confound with the industry expertise effect on KPI forecast accuracy, suggesting that analyst ability obtained via working experience (the nurture effect) is complementary to their intelligence or educational training (the nature effect).

To better understand the underlying mechanism linking industry expertise and KPI forecast accuracy, and its related effects, we conduct several additional analyses that *i*) exploit cross-sectional heterogeneity of the industries in which covered companies operate, *ii*) explore the different nature of KPI items, *iii*) investigate the capital market effects of KPI forecasts produced by industry expert analysts, and *iv*) conduct path analysis on the contribution of industry expertise in EPS forecasting via KPI forecasting.

First, we posit that knowledge benefits arising from direct industry expertise on KPI forecasting manifest in a more pronounced manner when equity analysts cover firms in industries that pose two characteristics. In particular, we argue that the advantage of industry expertise becomes more pronounced when covered firms operate in industries experiencing greater uncertainty, where analysts face incremental complexity in elaborating industry-specific information. Utilizing a measure of firm uncertainty based on sales volatility as developed by De Franco et al. (2023), we observe that the benefit of industry expertise on KPI forecast accuracy is statistically stronger among firms with high uncertainty compared to their counterparts. Similarly, we find that the effect of industry expertise in KPI forecasting concentrates among firms that experience rapid technological change. This is consistent with the notion that technical change prompt firms to change their operational strategy, product development, as well as new processes adopted in the manufacturing process, which can be challenging for non-expert analysts to interpret. Taken together, these findings support our hypothesis that industry expertise is beneficial to KPI forecasts because industry expert analysts are better equipped to understand covered firms' operations and to interpret KPI metrics than analysts who lack such expertise. In addition, this evidence speaks to the source of information to which industry expert analysts apply their knowledge to achieve better forecasting performance.

While industry characteristics differentiate the effect of industry expertise, we next focus on the KPI items and explore two types, namely, monetary-related and volume-related KPIs. The first category encompasses KPIs that measure the revenue generated or costs incurred by the firm per unit of output sold or input used. The second category includes KPIs that focus on the quantity of output produced or input used (e.g., inventories) during operations. We classify 35 KPIs as monetary-related and 44 as volume-related. This distinction is important as analysts typically integrate forecasts of pricing and volume, such as *Operating*

*Expenses per Available Seat Km* and *Available Seat Km*, when forecasting expected revenues and cost line items (Curtis et al., 2014). Hence, we examine the relationship between industry expertise and forecast accuracy for each category of KPIs to gain insights into the factors driving improved forecast accuracy among industry expert analysts. Our findings reveal that industry expert analysts are approximately 15% more precise in forecasting monetary KPIs compared to volume-related KPIs.

Motivated by these findings and related research suggesting that analysts are affected by macroeconomic dynamics in their decision-making and forecasting ability (Basu et al., 2010; Hugon et al., 2016), we develop an additional set of tests to examine the relative ability of industry expert and non-expert analysts to forecast monetary and volume KPIs in settings characterized by low and high unexpected inflation. We posit that given the uncertainty in price changes, industry expertise is more likely to confer a competitive advantage under high unexpected inflation scenarios. Our findings suggest that the benefits of industry expertise for KPI forecast accuracy are more pronounced when unexpected inflation is high. Further insights reveal that the enhanced performance of industry expert analysts under unexpected inflationary conditions is primarily driven by their superior ability to forecast monetary items compared to non-industry experts, as opposed to volume items. Unlike volume KPIs, which may be less sensitive to inflationary pressures, monetary KPIs necessitate a deeper understanding of how inflation affects pricing strategies and cost structures within specific industries. This underscores the critical importance of industry expertise for making accurate financial predictions in high unexpected inflation environments.

After establishing that industry expert analysts produce more accurate KPI forecasts, we delve into how the capital market perceives these forecasts. Utilizing stock market cumulative abnormal returns around KPI forecast revisions as a measure of informativeness, we compare the information content of expert and non-expert analysts' KPI forecasts. We confirm evidence from prior studies (e.g., Givoly et al., 2019) that both expert and non-expert KPI forecast revisions contain valuable information for investors. Furthermore, we find that the informativeness of expert-analyst KPI revisions is significantly larger than that of non-expert revisions. This finding aligns with the notion that analysts' industry expertise facilitates the understanding of KPI items, resulting in forecast revisions that contain more valuable information for investors. We obtain robust results when we exclude KPI forecast revisions issued around earnings announcements.

We then proceed to explore the extent to which industry expertise contributes to the accuracy of analysts' EPS forecasts through KPI forecasting. Employing path analysis, we model both the direct effect of industry expertise on EPS forecast accuracy and the mediating effect of KPI forecasts on EPS forecasts. Our analysis reveals that industry expertise generally enhances EPS forecasting performance (Bradley et al., 2017a). In addition, we observe an indirect effect of industry expertise on EPS forecasts through KPI forecasting, constituting nearly 20% of the overall effect. These findings underscore the significance of industry expertise in improving EPS forecasts, particularly through its influence on KPI forecast accuracy. These findings also help contextualize the evidence from Givoly et al. (2019), who document only a weak link between the *issuance* of KPI forecasts and EPS forecast accuracy. Specifically, our evidence suggests that there is a positive mapping between KPI forecast *accuracy* and EPS forecast accuracy, consistent with the evidence that KPI forecasts contain valuable information. This contradicts the notion that industry expert analysts have different forecasting goals or attention drivers than non-expert analysts, i.e., that industry expert analysts focus on KPI forecasts at the expense of EPS estimate accuracy. On the contrary, our evidence indicates that accurate industry expertise leads to higher EPS estimate accuracy also through a KPI forecast accuracy channel. Overall, these findings enrich our understanding of the mechanism linking industry expertise and EPS forecast accuracy and corroborate anecdotal evidence suggesting that more accurate KPI forecasts translate into more accurate EPS forecasts, given the critical role of KPIs in analysts' valuation models (PWC, 2007).

Our study can be of interest to both academic researchers and market participants. In a nutshell, our investigation contributes to the literature on analyst characteristics and their forecast performance. Given that prior studies have examined industry expertise of the analysts and their forecasting performance, our study differentiates in three perspectives.[2] First, and most importantly, our study speaks to the context via which analysts match their knowledge and expertise to specific company information to achieve better forecasting performance. Even though we are not among the first to explore the effect of analyst industry experience or expertise (Jacob et al., 1999), our study is among the first to explore the specific mechanism that transfers the expertise into better forecasting performance. Prior studies indicate that analyst industry knowledge is highly valuable to institutional investor clients and an important determinant of analyst compensation and their EPS forecasting performance (Brown et al., 2015; Brown et al., 2016; Bradley et al., 2017a). Our study indicates that industry expert analysts generate such value enhancement by better interpreting industry-related information via KPI items and incorporating such information into their forecasts. This novel finding extends the evidence of Bradley et al. (2017a) by clarifying *how* industry knowledge affects the EPS forecast.

Second, given the growing importance and adoption of non-financial reporting by managers, our study contributes to the scarce studies of KPI forecasts and more broadly studies that focus on non-financial disclosure of the firm. Given that investors pay most of their attention to financial performance indicators of firms (Clement, 1999), it is not surprising that the majority of extant studies on analysts' forecasts focus on analysts' estimates of fundamental financial metrics, either GAAP or non-GAAP financial indicators (e.g., GAAP EPS and Street EPS). On the other hand, firm disclosures do not merely refer to financial statements but include a rich variety of information on firms' products, supply chains, as well as operations, which facilitates the accuracy and interpretation of financial disclosure (Amir and Lev, 1996; Ittner and Larcker, 1998). Accordingly, investor demand for non-financial performance metrics has escalated in recent years, with operational KPIs being a prevalent type of non-financial disclosure provided by firms (Hand et al.,

[2] Previous studies have examined the impact of analyst industry expertise in various contexts. Gilson et al. (2001) observe that analysts with relevant industry experience at a subsidiary firm demonstrate enhanced forecast accuracy for firm subsidiaries following their separation from parent companies. Kadan et al. (2012) investigate the comparative skills of strategy analysts in ranking industries and find that these analysts exhibit superior cross-industry ranking abilities compared to their within-industry assessments. Bradley et al. (2017b) explore the oversight function of analyst industry expertise and provide consistent evidence that such expertise correlates with several positive outcomes. These include lower earnings management, a reduced likelihood of financial misrepresentation, diminished CEO excess compensation, and increased CEO performance-turnover sensitivity.

2022). Our study enriches the KPI literature by providing evidence of how industry expertise can be coupled with KPI disclosure to better serve the needs of the capital market participants.

Finally, our study yields better generalizability than other related academic research, also due to the comprehensive nature of the data sources we utilize. First, we take advantage of FactSet's Standard DataFeed Estimates which offers much broader coverage of KPI forecasts issued by analysts than other conventional databases such as I/B/E/S. Importantly, FactSet data are also less prone to analyst self-reporting bias, as the data vendor collects forecast information directly from the published analyst reports. Second, FactSet aggregates information on analysts' historical working experience from a variety of sources, enabling a comprehensive measurement of analyst industry expertise. In contrast, frequently employed career data obtained from social media sources only (e.g., LinkedIn) are more prone to a voluntary disclosure bias and are likely endogenous to analysts' incentives and ability, thus potentially contaminating regression results.

In general, many analyst-related features have been identified as determinants of analyst forecast accuracy.[3] Our research differentiates from these studies and is most pertinent to the research examining analysts' information processing ability (Bradshaw, 2009), echoing the call in Schipper (1991) and Brown (1993) that the literature should focus more on the context within which analysts make their decisions (Clement, 1999; Clement et al., 2007). To the extent that the specific information source in corporate disclosure that facilitates analyst forecast performance remains a "black box", our study sheds light on the topic by showing that analysts significantly rely on operational KPI information. We demonstrate that relevant industry experience facilitates the interpretation of industry-specific KPIs, enabling their effective incorporation into financial performance forecasts.

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[3] Hilary and Shen (2013) shed light on how the analyst learning experience about the target firm, through attention to managerial guidance, enhances forecast accuracy. Bilinski et al. (2013) corroborate this finding using an international sample. Another strand of literature delves into the influence of analyst behavioral bias (Hilary and Menzly, 2006; Ramnath et al., 2006; Dolvin et al., 2009; Cen et al. 2013; Jiang et al. 2016; Cuculiza et al., 2021; Lo and Wu, 2018). Bourveau and Law (2021) uncover how disruptive life events shape analysts' perceptions of firm risk due to the availability heuristic. Similarly, deHaan et al. (2017) reveal that local weather conditions influence analysts' efforts in issuing forecast revisions. Gu et al. (2019) highlight the benefits of social connections between financial analysts and mutual fund managers for both parties, while Lourie (2019) identifies the impact of analysts' career concerns on forecast bias for firms they are connected to (i.e., the "revolving door" effect). Christensen et al. (2017) illustrate how analysts with political connections enjoy easier access to value-relevant information. Jung et al. (2015) find a relationship between analyst interest in a firm and its future fundamentals, capital market activities, and stock returns, further enriching our understanding of analyst behavior and its implications.

## 2. Data, Sample, and Variables

### 2.1 FactSet Data on KPI Forecasts and Analysts' Background

Our analysis predominantly relies on FactSet's Standard DataFeed Estimates dataset, which encompasses analysts' estimates of firms' financial line items and operational KPIs. As for conventional financial line items, data on operational KPIs include information on the issuing analyst, his brokerage house, the forecast issuance date, the related fiscal period, as well as the forecasted and actual figures. The KPI forecasts provided at the quarterly level span from 2009 onwards.

FactSet data on analysts offer several potential advantages over those provided by other data sources, including I/B/E/S. First, while many studies rely on I/B/E/S forecasts and recommendations, recent research suggests that I/B/E/S data have some limitations. For instance, Call et al. (2021) document data inconsistencies in the database due to changes imposed by contributing brokerages. In that vein, FactSet circumvents this bias by directly collecting forecasts from published analyst reports, bypassing direct brokerage interactions. Second, Thomson Reuters' policy change poses challenges in data analysis by shuffling brokerage and analyst identifiers over time, hindering the identification of analysts' backgrounds and experiences. Third, and importantly, I/B/E/S data has limited coverage of analyst forecasts on KPI items, likely due to its reliance on voluntary self-reporting of forecasts from analysts. Notably, we observe that FactSet covers roughly 2.5 times as many KPIs as I/B/E/S. The relative scarcity of studies focusing on KPI forecast attributes to date potentially originates from this limited data availability.

For identifying analysts' experience, we rely on the FactSet People dataset, which includes profiles of over 4.2 million individuals connected to more than 1.5 million firms. Information in the database is captured from online resources, regulatory filings, and press releases, employing a combination of technology and human processes. The FactSet People dataset encompasses personal details such as educational and professional backgrounds, contact information, and charitable engagements. This dataset offers several advantages for our study. First, by sharing identifiers with FactSet's Standard DataFeed Estimates dataset, it facilitates straightforward association with forecast data and reduces the risk of mismatches. Second, it provides comprehensive information on employers, including their industry affiliation, which is critical information we use to define analyst industry expertise.

## 2.2 Sample

We initiate our sample construction process from the KPI quarterly forecast dataset, encompassing over 17.1 million observations. This dataset includes forecasts on 163 distinct KPI items, pertaining to 4,350 unique publicly-traded firms in the United States. These forecasts are provided by 5,660 unique analysts representing 730 brokerage houses.

We filter out observations where the actual value of the forecasted item is not available (14.7 million observations left) and those without reported forecast publication dates (12.6 million observations left). Following related research (Bissessur and Veenman, 2016), we keep forecasts with a maximum (minimum) horizon of 180 (2) days from the actual KPI announcement date to minimize the effect of stale forecasts and potential information leakage (4.5 million observations left). Further, in order to compute KPI forecast errors, we only rely on the last forecast issued by an analyst for a specific KPI and firm before the fiscal quarter-end (1.8 million observations left). In line with related literature on KPI forecasting (Givoly et al., 2019), we drop observations related to firms in the financial industry and non-industry-specific KPIs. We exclude KPIs relevant to the financial industry and those lacking industry specificity because the majority of these KPIs can be directly inferred from financial statements (569,772 observations left).[4] We then require baseline firm and analyst control variables to be available (416,685 observations left) and each KPI to have a minimum of 20 forecasts and at least 2 forecasts per KPI-firm-quarter. This final requirement is designed to ensure that the KPI is of sufficient economic importance. Our final sample consists of 1,208 unique firms, 1,840 unique

[4] For example, the most prevalent items categorized by FactSet as KPIs, either relevant to the financial industry or lacking industry specificity, include: Operating Expenses, Net Interest Income, Provisions for Loans, Cost to Income Ratio, and Net Loans.

analysts from 323 unique brokerage houses, 79 KPI items, and 381,128 firm-analyst-KPI-quarter observations. Table 1 provides the steps through which we reach the final sample for our main analysis. Appendix A lists the 79 KPI items.

## 2.3 Variables

### *2.3.1 KPI Forecast Error*

Our main dependent variable is the *KPI Forecast Error*, computed as the absolute difference between the analyst's *i* forecast of KPI *k* for firm *j* in quarter *t* and the actual value of the forecasted item, divided by the average absolute value of the two variables (Givoly et al., 2019). We also present results using an alternative forecast error measure, the *KPI Proportional Mean Absolute Forecast Error* (*KPI PMAFE*) developed by Clement (1999) and widely used in previous studies (e.g., Bradley et al., 2017a; Bourveau et al., 2024). Specifically, *KPI PMAFE* is the difference between the absolute forecast error (*AFE*) of analyst *i* for KPI *k* and firm *j* in quarter *t* and the mean absolute forecast error for KPI *k* and firm *j* in quarter *t*. This difference is then scaled by the mean absolute forecast error for KPI *k* and firm *j* in quarter *t*.

### *2.3.2 Analyst Industry Expertise*

The focal variable of interest of our study is the analyst industry expertise, which is constructed following the methodology outlined in Bradley et al. (2017a). Analysts are categorized as industry experts if they cover firms within the same Fama-French industry classification group as those where they were previously employed before becoming analysts. To operationalize this, we extract 4-digit SIC industry codes for both the firms followed by the analysts and those associated with the analysts' prior work experience. These codes are then grouped into five distinct Fama-French industries. Our main independent variable, *Industry Expertise*, is an indicator variable taking the value of one if the Fama-French industry of the firm followed by the analyst matches with any of the Fama-French industries of the firms where the analyst previously worked.

Additionally, we explore alternative variables capturing analyst industry expertise. First, we introduce a continuous variable, *Years Industry Expertise*, which measures the number of years the analyst worked for a firm within the same Fama-French industry classification group as the firm he covers. Second, we utilize a more detailed classification of industry participation based on the 10 major industry sectors classified by the SIC system and define a corresponding expertise indicator variable (*Industry Expertise SIC*).

### *2.3.3 Control Variables*

We include a set of firm, analyst, and brokerage variables in our multivariate tests, drawing from prior studies (O'Brien and Tan, 2015; Bradley et al., 2017a). Firstly, we include *Analyst Tenure*, which indicates the length of an individual's tenure as an equity analyst. Similarly, *Analyst Firm Specific Tenure* measures the duration in years that an analyst provides forecasts for a specific firm, reflecting his depth of understanding of the company's dynamics. We also consider *Firms Covered*, representing the number of firms covered by an analyst in a given quarter, and *Industries Covered*, indicating the range of industries in which the firms covered by an analyst operate. Financial metrics such as the *BTM* and firm *Size*, represented by the logarithm of the total assets of the covered firm, are also included as controls. Additionally, we incorporate *Quarterly Return*, calculated as the buy-and-hold stock return minus the equal-weighted market return during the 90 days leading up to the forecast, and *Analyst Coverage*, denoting the number of analysts covering a firm in a given quarter. *Forecast Horizon* represents the number of days between the analyst's forecast and the actual release date of the KPI, accounting for the time lag between forecasting and realization that may impact prediction accuracy. Finally, the *Top Broker Dummy* is included as a binary variable indicating whether the analyst is affiliated with a top decile brokerage house.

In addition, we include a set of fixed effects tailored to the specific tests we conduct. Our main specification includes analyst-by-quarter fixed effects, as well as fixed effects for KPIs and firms. This allows us to control for time-varying characteristics specific to individual analysts over different quarters, such as workload and attention (Bourveau et al., 2024), as well as time-invariant characteristics specific to each KPI and firm, such as inherent differences between KPIs and idiosyncratic features of individual firms that could influence the dependent variable. We also present results using another two sets of fixed effects, namely, analyst, firm, quarter, and KPI fixed effects, and analyst, firm-by-quarter, and KPI fixed effects.

## 2.4 Summary Statistics and Univariate Test

Table 2 Panel A provides the summary statistics of the dependent variable and the independent variable, along with control variables. We present the mean, median, standard deviation, lower and upper quartile for each of them. In addition, we provide the univariate comparisons of the variables related to KPI forecasts issued by industry expert and non-expert analysts. Among the industry expert sample, the average *KPI Forecast Error* is 0.101, with a median of 0.027 and a lower (upper) quartile of 0.007 (0.080). On average, industry experts have 5.8 years of working experience in the reference industry, with approximately 26.4% also having experience in an unrelated industry. Turning to the control variables, the average firm size is $4.5 billion, exhibiting wide variation from the lower quartile ($1. 6 billion) to the upper quartile ($12. 8 billion). The *BTM* averages 2.875 with a median of 1.757. The average quarterly stock return in the sample is 2.8%, and firms have an average of 18 analysts covering them. Individuals in the sample possess an average of roughly 9.3 years' experience as analysts, as captured by the FactSet data, and each analyst covers on average 19 firms. The *Forecast Horizon* of KPI forecasts is, on average, 48 days, with approximately 73% issued by analysts affiliated with a top brokerage house.

Comparing the sample of non-expert analysts to the expert analyst sample reveals several notable differences. Non-expert analysts tend to exhibit higher *KPI Forecast Error*, cover more firms, and are associated with smaller firms characterized by higher BTM and lower stock returns. In addition, non-expert analysts are less likely to work at a top brokerage house and update KPI forecasts less frequently, resulting in older forecasts compared to those of industry experts. Overall, these comparison results suggest that analyst industry expertise is not randomly assigned to firms, consistent with the notion that brokerage houses match certain firms with industry expert analysts. We address the potential selection bias in a later section.

Panel B presents the distribution of *KPI Forecast Error* categorized by the industry of the sample firms, with industry categorization based on both the 5 Fama-French industries and the 10 SIC industry classifications. According to the Fama-French classification, the largest industry group is *Manufacturing, Energy, and Utilities*, representing roughly 53% of the sample, while the smallest group comprises *Healthcare, Medical Equipment, and Drugs*. We observe some variations in forecast error between the industries. For instance, the average forecast error is 7.6% in *Other* industry and 34.7% in *Consumer Durables, Nondurables, Wholesale, Retail, and Some Services*. Turning to the SIC 10 industry grouping, *Mining* emerges as the largest category, encompassing 56% of the total observations, while *Agriculture, Forestry, and Fishing* represent the smallest category. Again, we observe that the *KPI Forecast Error* varies from 2.1% in *Finance, Insurance, and Real Estate* to 47.5% in *Wholesale Trade*.[5]

Panel C presents information on the 30 most widely forecasted KPIs. We show that, for example, *Production Per Day* in the *Mining* industry is the most prevalent KPI, followed by *Same Stores Sales – Total* in the *Retail Trade* industry. The forecast error for these KPIs spans a wide range, from 1.8% to 58.9%, suggesting significant heterogeneity across industries and distinctiveness among KPIs.

In Panel D, we showcase statistics on the number of KPI items forecasted by analysts for each Fama-French industry, juxtaposing expert and non-expert analysts. Remarkably, non-expert analysts tend to issue a larger number of KPIs forecasts than expert analysts across most industries. Panel E presents the percentage of KPI forecasts issued by analysts for each industry group, comparing experts and non-experts.

[5] Since we drop firms in the financial sector, observations in the *Finance, Insurance and Real Estate* industry pertain to *Real Estate*.

Unsurprisingly, we find that most of the KPI forecasts are issued by non-experts, with the *Other* industry showing the smallest difference between the two groups. Overall, at the sample level, expert analysts account for 16.5% of KPI forecasts. Finally, in Panel F we showcase the distribution of the KPI items forecasted by the reference industry of the expert analyst. Notably, the last column highlights the proportion of KPI items forecasted by expert analysts outside of their reference industry. For instance, experts in *Manufacturing and Consumer Goods* provide the majority of their KPI forecasts (85%) for firms within their reference industry, while *Healthcare* industry experts issue a larger proportion (62%) of KPI forecasts for firms in other industries. One potential explanation for this pattern is the distinctiveness of industries, which may limit experts from applying their knowledge across different sectors.

## 3. Analyst Industry Expertise and KPI Forecast Accuracy

### 3.1 Main Results

We run the following OLS regression examining the effect of analyst industry expertise on their KPI forecast accuracy:

$$\textit{KPI Forecast Error}_{ikjt} = a + \beta_1 \times \textit{Industry Expertise}_{ijt} + \sum \beta \times \textit{Analyst Level Controls}_{ijt} + \sum \beta \times \textit{Firm Level Controls}_{jt} + \sum \beta \times \textit{Forecast Level Controls}_{ikjt} + \sum \textit{Fixed Effects} + \zeta \qquad (1)$$

where $k$ represents the KPI item, $i$ represents the analyst, $j$ represents the covered firm, and $t$ represents the quarter.

Table 3 presents the main results. In Column (1), we include only control variables known from prior studies to be associated with forecast accuracy. We observe a negative and highly significant coefficient for *Industry Expertise* at the 1% level (t-statistic = -19.01). Moving to Column (2), where we incorporate firm, analyst, quarter, and KPI fixed effects, we still find a negative and significant effect of analyst industry expertise at the 1% level (t-statistic = -4.78). Columns (3) and (4) repeat the tests using different fixed effect structures. Specifically, in Column (3), we employ analyst, firm-by-quarter, and KPI fixed effects, while in

Column (4), we utilize the baseline fixed effect structure of analyst-by-quarter, firm, and KPI fixed effects. In both specifications, we find a negative and significant coefficient at the 1% level. Based on the results from Column (4), we document that, on average, the *KPI Forecast Error* is 27% lower when the analyst possesses corresponding industry expertise compared to analysts without matching expertise. Turning to the control variables, our findings align with prior research. For instance, larger firms and those covered by a greater number of analysts tend to exhibit significantly lower KPI forecast errors. Overall, our findings remain robust across various specifications, demonstrating that analyst industry expertise is consistently associated with higher KPI forecasting accuracy. This supports our main hypothesis.

### 3.2 Identification

The results above are potentially subject to endogeneity concerns (McNichols and O'Brien, 1997). Specifically, the choice of firm coverage by brokerage houses and analysts may be influenced by many factors that are related to industry expertise. For instance, firms with more stable prospects may be more likely to attract industry expert analysts. Alternatively, analysts with specialized knowledge of certain industries may receive greater support and resources from their brokerage houses, allowing them to dedicate more time and effort to analyzing companies. To the extent that the fixed effects used in our analysis fail to adequately account for these omitted variables, our inferences could be confounded.

In order to address these concerns, we adopt an identification strategy that relies on difference-in-differences (DiD) estimation, leveraging the closure of brokerage houses' research departments (Kelley and Ljungqvist, 2012) and analyst retirements (Gokkaya et al., 2023). For our purposes, successful identification relies on terminations of coverage inducing a reduction in industry expert analyst coverage. To identify broker closures between 2009 and 2021, we proceed as follows. First, we utilize FactSet data to compile a list of brokerage houses in our sample that ceased providing financial or KPI forecasts. Second, we conduct searches on Factiva, the Financial Industry Regulatory Authority's (FINRA) BrokerCheck database, and other online financial news platforms such as Bloomberg Businessweek to gather information on the closures and the closure dates. We exclude merger-induced broker closures because post-merger analyst retention and stock coverage may be influenced by analyst characteristics (Wu and Zang, 2009), as well as closures exclusively affecting non-expert analysts. To identify retirements of industry expert analysts, we focus on cases unrelated to broker events where an expert analyst ceases to provide forecasts at the age of 65 or above. Analyst retirement is often driven by age and personal considerations, making it arguably exogenous to coverage decisions.

Building on previous research (Hong and Kacperczyk 2010; Fung et al., 2023.), we utilize a one-year window to identify treatment firms affected by the termination of expert analyst coverage resulting from either brokerage house closures or analyst retirements. If a firm receives coverage from the closed broker or the retired analyst during the one-year window before the termination date, it is designated as a treatment firm. Subsequently, for each treatment firm, we implement propensity score matching to identify the closest control firm that did not experience analyst coverage termination. This matching process is based on Fama-French 5 industry classification, *BTM*, and firm *Size* as of the quarter prior to the coverage termination event. Our sample encompasses 47 event-firm instances of expert analyst coverage termination attributable to brokerage closures and 43 event-firm instances related to analyst retirements. Leveraging this sample, we conduct DiD analysis in the three-year window around coverage termination based on the following specification:

$$Mean\ Forecast\ Error_{jt} = a + \beta_1 \times Post_{jt} \times Treatment_j + \sum \beta \times Firm\ Level\ Controls_{jt} + \sum Fixed\ Effects + \zeta \qquad (2)$$

where *Mean Forecast Error* is the average KPI forecast error for firm *j* in quarter *t*. *Treatment* denotes firms affected by a termination of coverage by an industry expert analyst, and *Post* denotes the quarters after this termination. We include firm, quarter, and termination event fixed effects.

Table 4 presents the results. In Column (1), we examine the impact of the brokerage house closure as the exogenous shock. We find that treatment firms encounter an increase in KPI forecast error relative to the control sample. Turning to Column (2), where we consider cases of analyst retirements as the treatment, we observe similar findings. Following the loss of analyst coverage due to retirement, the average KPI forecast error tends to increase. In Column (3), we combine both types of shocks and find consistent results. Based on the regression coefficient from this column and considering that the average *Mean Forecast Error* equals 0.186, we conclude that the KPI forecast error increases by about 39% following the termination of expert analyst coverage. We present a plot of the coefficient of interest by year in Figure 1, which shows that while our identification strategy is not perfect, significant treatment effects in the direction of our predictions are largely concentrated after the event of brokerage closure or analyst retirement. Overall, our identification test indicates a significant effect of industry expertise of analysts on KPI forecast accuracy, suggesting a causal rather than associational nature.

## 3.3 Robustness Checks

We conduct several tests to assess the robustness of the main results. We present the related findings in Table 5. First, we investigate if our results differ when using alternative measures capturing analyst industry expertise and KPI forecast error. In Panel A, Column (1), we show that our results remain robust when employing a measure of industry expertise based on SIC 10 industry classifications instead of Fama-French 5 industries. In Column (2), we observe consistent findings when utilizing a continuous measure of industry expertise (instead of an indicator variable), represented by the number of years the analyst has worked in the related industry.[6] Figure 2 depicts the findings graphically. Economically, we find that every additional year of working experience in the industry is related to a 5.6% decrease in *KPI Forecast Error*. In Column (3), we

[6] We experience a reduction of approximately 30,000 observations in our analysis when using *Years Industry Expertise* as a variable. This reduction occurs because while we can observe the previous employment of industry expert analysts, we are unable to measure the length of their employment in some instances. As a result, we opt to exclude these observations from this segment of the analysis.

use an alternative measure of forecast error, *KPI PMAFE*, as the dependent variable. The findings align with those from the main test.

In Panel B, we alter the specification to conduct the examination using different aggregation approaches, namely, the analyst-firm-quarter level, the KPI-firm-quarter level as well as the firm-quarter level. Accordingly, we aggregate the forecast accuracy measure at each level by averaging the forecast errors. For the analyst-firm-quarter level analysis, no changes to the regressors are required. However, for the KPI-firm-quarter and firm-quarter level analyses, we convert the primary independent variable to be the ratio of analysts covering a firm who are industry experts (*Proportion Expert Analysts*). In addition, we drop firm coverage and tenure as controls since these are defined at the analyst level. In Column (1), we find that the coefficient of *Industry Expertise* is negative and significant at 5% (t-statistic = -2.41). Since the average value of the KPI forecast errors aggregated at the analyst-firm-quarter level is 0.202, this indicates that industry expert analysts have a 24.5% lower forecast error than non-expert analysts. In Columns (2) and (3), where we conduct the analysis at the KPI-firm-quarter and firm-quarter levels respectively, we find the coefficients on the *Proportion Expert Analysts* ratio are negative and significant at 1% level in both specifications. Economically, the results suggest that a one-standard-deviation increase in the ratio of the analyst industry expertise is associated with a 17.5% and 12.9% lower forecast error according to the estimate in Columns (2) and (3), respectively.[7]

Two personal features of equity analysts could significantly overlap with industry expertise and thus confound our inferences. First, expert analysts may produce better operational KPI forecasts not because they have a more profound understanding of their reference industry, but due to their general training in corporate environments. To disentangle these two components of pre-analyst job experience, we augment our baseline regressions with variables capturing pre-analyst job experience in an unrelated industry (Bradley

[7] We calculate this economic significance as follows. One standard deviation of the industry expertise ratio equals 0.227 and 0.235 when observations are captured at the KPI-firm-quarter and firm-quarter levels, respectively. The aggregated average KPI forecast error equals 0.167 and 0.208 when observations are captured at the KPI-firm-quarter and firm-quarter levels, respectively. Consequently, considering coefficients from columns 2 and 3 of Table 5B, we obtain 0.227 × 0.129 / 0.167 = 0.175 and 0.235 × 0.114 / 0.208 = 0.129.

et al., 2017). We report results in Columns (1) and (2) of Table 5, Panel C, where we respectively define *Unrelated Industry Expertise* based on the Fama-French 5 and the SIC 10 industry groupings. We find that the coefficient on *Industry Expertise* remains significant and negative in both specifications. *Unrelated Industry Expertise* is also negatively associated with *KPI Forecast Error*, although the economic magnitude and statistical significance of this relationship are more limited. Second, we focus on the analysts' educational background, as it may correlate with their industry expertise. As such, the industry expertise of analysts may simply reflect their educational attainments or intellectual capability. In order to filter out this alternative explanation, we include control variables in our baseline regression indicating whether the analyst holds a post-undergraduate degree (e.g., Master's, MBA, or PhD) and attended a prestigious university from the Ivy League (Useem and Karabel, 1986; Domhoff, 2002). Results presented in Columns (3) and (4) confirm that industry expert analysts issue more accurate KPI forecasts. Additionally, they indicate that the educational prestige or credentials of analysts are not associated with greater KPI forecast accuracy. Overall, the evidence in Table 5 supports the robustness of our main findings, indicating that analysts' industry expertise enhances the accuracy of their KPI forecasts.

## 4. Industry Variations, KPI Category, and the Effect of Industry Expertise

### 4.1. Industry Variations

To deepen our understanding of how industry expertise influences KPI forecast accuracy, we explore three scenarios where analyst expertise is expected to yield significant benefits. First, we posit that the forecasting benefits of industry expertise should be amplified if the firm belongs to an industry with high uncertainty. Intuitively, industries with high uncertainty often present complex dynamics, rapid changes, and diverse factors affecting performance. In such environments, analysts with deep industry expertise are better equipped to discern drivers impacting KPIs. Second, we propose that in industries with high levels of R&D investments, where technological advancements occur at a faster pace compared to industries with low R&D

investments, analyst industry expertise becomes particularly valuable. Analysts with specialized knowledge in such sectors can better grasp the relationship between technological developments and corporate operational performance. For example, they can assess whether R&D investments primarily drive sales growth through the introduction of innovative products or contribute to cost reduction through the implementation of efficient processes. Finally, we argue that in industries characterized by high reporting complexity, expert analysts are better equipped to interpret the disclosed information to map operations to performance metrics. To investigate these scenarios, we conduct cross-industry analysis, partitioning our sample based on industry-level measures of uncertainty, R&D investments, and accounting reporting complexity. Specifically, we rely on i) a measure of industry uncertainty, calculated as the average sales volatility of firms within an industry over the 16 quarters leading up to a given quarter (De Franco et al., 2023), ii) the quarterly average ratio of *R&D Expenses* to *Total Sales* in the industry, and iii) the industry quarterly average of the accounting reporting complexity measure developed by Hoitash and Hoitash (2018).

We present the results in Table 6. In Columns (1) and (2), we compare the subsamples of high and low industry uncertainty levels. Columns (3) and (4) depict the results when we split the sample by the degree of technological advancements within industries. In Columns (5) and (6), we explore the differences between industries with high and low financial reporting complexity. First, in Columns (1) and (2), we observe a negative association between industry expertise and KPI forecast error in both high and low industry uncertainty subsamples. However, an F-test reveals that the coefficient on *Industry Expertise* is significantly more negative in the high uncertainty subsample. This supports our conjecture that industry expertise is incrementally helpful in industries with high uncertainty. Turning to the next cross-industry comparison, the results in Columns (3) and (4) indicate that the impact of industry expertise on KPI forecast accuracy concentrates in settings experiencing high technological change (F-test significant at the 1% level). Finally, we compare firms operating in industries with high and low financial reporting complexity. We find that the negative effect of *Industry Expertise* on KPI forecast error is significant at the 1% level among complex reporting firms in Column (5), while it is insignificant among low complexity firms in Column (6). However, an F-test indicates that the difference is statistically insignificant. Overall, the results in Table 6 suggest that the benefit of industry expertise is contingent on the nature of the industry, aligning with our expectations regarding when the effect is likely to be stronger.

### 4.2 Monetary vs. Volume KPIs

When forecasting expected financial line items, such as revenues or costs, analysts often integrate operational KPI forecasts of volumes and monetary amounts (Curtis et al., 2014). For instance, multiplying expected *Available Seat Km* (*ASK*) by *Operating Expenses per ASK* enables analysts to forecast operating expenses for airline firms. Similarly, multiplying *Production per Day* by *Realized Price* allows analysts to forecast revenues for companies in the energy sector. Building on this premise, we examine the relationship between industry expertise and forecast accuracy for volume and monetary-related KPIs to gain further insights into the factors driving improved forecast accuracy among industry expert analysts.

We categorize KPIs in our sample according to this framework, identifying 35 KPI items (154,515 observations) as monetary-related and 44 KPI items (229,089 observations) as volume-related. Table 7 presents the 15 most commonly forecasted KPIs for each category. Monetary-related KPIs encompass metrics that gauge the revenue generated (*Revenues per Unit*) or costs incurred (*Costs per Unit*) by the firm per unit of output sold or input used. Volume-related KPIs, on the other hand, include measures of resources put into a process, such as capital and labor, serving as precursors to performance (*Inputs*) or metrics quantifying the volume of products or services a company is projected to successfully deliver to its customers (*Outputs*).

To explore the relationship between industry expertise and forecasting accuracy for different KPI categories, we modify the baseline regression model. First, we augment the model by including the interaction between *Industry Expertise* and *Monetary KPI*, an indicator that denotes forecasts relating to monetary KPIs.

The regression outcomes presented in Column 1 of Table 8, Panel A, reveal that the coefficient on the *Industry Expertise* × *Monetary KPI* interaction is negative and statistically significant at the 10% level. This result suggests that industry expert analysts are approximately 15% more precise in forecasting monetary-related items compared to volume-related items.[8] Second, we delve deeper into different KPI subcategories and examine the relative forecasting accuracy of industry expert analysts with respect to *Revenues per Unit*, *Costs per Unit*, *Inputs*, and *Outputs* items. The results in Column 2 of Table 8, Panel A, suggest that it is in the domain of input-related KPIs where industry expert analysts lose their forecasting competitive advantage over non-expert analysts. Specifically, while the interactions between *Industry Expertise* and *Revenues per Unit*, *Costs per Unit*, and *Outputs KPIs* are negative and statistically significant at the 1% level, the *Industry Expertise* × *Inputs KPI* interaction is positive and not statistically significant at conventional levels. Input metrics may be more susceptible to influences from operational efficiencies, technological capabilities, and future expansion plans, factors that are inherently challenging to predict even with industry expertise.

Motivated by these findings and related research suggesting that analysts are affected by macroeconomic dynamics in their decision-making and forecasting ability (Basu et al., 2010; Hugon et al., 2016), we conduct an additional set of tests to assess the relative ability of industry expert and non-expert analysts to forecast monetary and volume KPIs in settings characterized by low and high unexpected inflation. We hypothesize that industry expertise is particularly advantageous amidst high unexpected inflation scenarios due to the uncertainty in price developments. Following related research (Binz et al., 2023), we identify high unexpected inflation scenarios as those quarters with a larger than median difference between realized and consensus inflation forecasts. In Table, 8 Panel B, we examine this hypothesis for the entire set of KPI forecasts and separately for monetary and volume KPIs. The results in Columns (1) and (2) suggest that the benefits of industry expertise for KPI forecast accuracy are more pronounced during periods of high unexpected inflation compared to low inflation, reaffirming the notion that industry expert analysts

[8] We calculate this amount scaling 0.024 by 0.158, the average *KPI Forecast Error*.

outperform non-experts in settings characterized by greater uncertainty. Further insights from Columns (3) to (6) reveal that the enhanced performance of industry expert analysts under unexpected inflationary conditions primarily stems from their superior ability to forecast monetary items compared to non-industry experts, as opposed to volume items. Unlike volume KPIs, which may be less sensitive to inflationary pressures, monetary KPIs require a deeper understanding of how inflation affects pricing strategies and cost structures within specific industries. This highlights the critical significance of industry expertise in accurately predicting outcomes in environments characterized by high unexpected inflation.

## 5. Analyst Industry Expertise and EPS Forecast

In light of prior studies documenting the positive impact of analysts' industry expertise on earnings forecast accuracy (Bradley et al., 2017a), and considering our findings that expert analysts issue more accurate forecasts on KPI items, we aim to explore the relative contribution of industry expertise to earnings forecast accuracy through a KPI forecast accuracy channel.

To investigate this mechanism, we employ path analysis. In performing the path analysis, we aggregate KPI forecasts at the analyst-firm-quarter level (as in Table 3B, Column (1)), and estimate a structural equation model (SEM) of the direct effect of *Industry Expertise* on *EPS Forecast Error,* as well as its indirect effect through the aggregated KPI forecast error as a mediating variable. The SEM estimation comprises two regressions: a regression of *EPS Forecast Error* on *Industry Expertise* and the mediating variable, *Mean KPI Forecast Error*, and a regression of *Mean KPI Forecast Error* on *Industry Expertise*, with both regressions controlling for the set of variables presented in Table 3B, Column (1). The indirect effect of *Industry Expertise* on *EPS Forecast Error* is the product of the effect of *Industry Expertise* on the mediating variable and the effect of the mediating variable on *EPS Forecast Error*.

The results of the path analysis are presented in Table 9 and visually depicted in Figure 3. Consistent with previous research findings (Bradley et al., 2017a), our analysis reveals that *Industry Expertise* has a significant negative total effect on *EPS Forecast Error* (-0.043, significant at the 5% level). Notably, we find that almost 20% of this total effect is mediated through KPI forecasting accuracy (-0.007, significant at the 1% level).

This finding is important for several reasons. First, Givoly et al. (2019) document a weak link between the *issuance* of KPI forecasts and EPS forecast accuracy. We instead observe a strong relationship between the two types of forecasting accuracy, suggesting that non-financial disclosure contains valuable information about a firm's financial performance. In addition, our results indicate that it is the industry expertise of the analysts that facilitates such improvement, thus helping to reconcile their findings and ours. On the other hand, Bradley et al. (2017a) document the substantial impact of industry expertise of analysts on EPS forecast accuracy while remaining silent on the mechanism through which this effect manifests. In this regard, our results supplement their study by pinpointing a relevant channel through which analysts with specialized industry knowledge leverage operational information to improve their financial forecasts.

**6. Informativeness of KPI Forecast**

Theory predicts that investors' response to forecast revisions increases with the accuracy of the forecast (Abarbanell et al., 1995), a notion supported by empirical research (Stickel, 1992; Park and Stice, 2000; Gleason and Lee, 2003). However, the literature also suggests that not all analyst characteristics linked to forecast accuracy are associated with return responses to forecast revisions (Clement and Tse, 2003). To evaluate the market assessment of industry expertise in KPI forecasting, we develop a test of the capital market reactions to KPI forecast revisions by expert and non-expert analysts. Specifically, we rely on the following OLS regression:

$$CAR\ (-1,+1)_{ikjt} = a + \beta_1\ Industry\ Expertise_{ijt} \times Signed\ KPI\ Revision_{ikjt} + \beta_2 \times Signed\ KPI\ Revision_{kjt} + \beta_3 \times Industry\ Expertise_{ijt} + \beta_4 \times EPS\ Revision_{kjt} + \sum \beta \times Analyst\ Level\ Controls_{ijt} + \sum \beta \times Firm\ Level\ Controls_{jt} + + \sum Fixed\ Effects + \zeta \qquad (3)$$

where the dependent variable is the cumulative abnormal return (*CAR*) within the 3-day window centered around the announcement date of the revision.[9] The *KPI Revision* variable is computed as the difference between the newly issued KPI forecast of item *k* by analyst *i* for firm j at time t and the previous corresponding forecast issued by the analyst. This difference is then scaled by the average absolute value of the two variables (Givoly et al., 2017). We convert *KPI Revision* into *Signed KPI Revision* by multiplying them by -1 if the KPI item negatively maps into the firm's accounting performance (e.g., *Operating Expenses per ASK* item). Thus, a more positive revision value is expected to be associated with a greater value of announcement *CAR*. In order to compare expert and non-expert analysts, we include the interaction term of *Industry Expertise* and *Signed KPI Revision*. To address the effect of simultaneous financial item revisions, we control for the EPS forecast revision issued by an analyst on the same date as the KPI revision. For robustness, we also conduct the analyses at the analyst-firm-revision date level, aggregating KPI revisions issued on the same date for a firm by an analyst. Moreover, to further mitigate potential confounding effects, we develop an analysis that excludes revisions issued on the same days as earnings announcements.

We present the results in Table 10. In Column (1), considering the entire sample of KPI revisions, we observe a positive and significant coefficient on the interaction term at the 1% level. This supports the notion that KPI revisions carry more weight when issued by industry experts than non-expert analysts. In Column (2), when we exclude dates coinciding with earnings announcements, the pattern persists, indicating that analyst industry expertise continues to enhance the informativeness of the KPI revisions to the capital market. In Columns (3) and (4), where we aggregate data at the analyst-firm-revision date level, we derive similar conclusions as those from the KPI level tests. Economically, relying on the specification in Column (4), industry experts elicit a 0.27% higher market reaction than non-expert analysts at the level of the average KPI revision. Regarding the control variables, we find results consistent with expectations and prior studies. For instance, we find that the coefficient on *Signed KPI Revision* is positive and significant, indicating KPI

[9] Abnormal return is computed as the daily holding return minus the value-weighted market portfolio return.

forecasts contain valuable information about firm performance. In addition, we consistently find that EPS revisions are informative. This finding is important because it suggests that KPI revisions reveal unique incremental information beyond what is contained in earnings forecasts alone. Overall, Table 10 shows that industry expertise in KPI forecasting is valued by the capital market, as KPI forecasts from expert analysts are more informative than those from non-experts.

**7. Conclusions**

In this study, we present several insights into how analyst industry expertise enhances operational KPI forecasting performance. Our study addresses a timely question, given the increasing demand from investors and market participants for non-financial disclosure from firms in recent years. We posit that analyst industry expertise plays a pivotal role in deepening their understanding of firm operations, primarily through a more profound comprehension of the industry environment and trends.

In our main analysis, we establish a positive association between analyst industry expertise and superior KPI forecast performance. Leveraging exogenous coverage terminations, we document that this heightened forecasting performance causally originates from analyst industry expertise. Importantly, we rule out the alternative explanation that this effect stems solely from alternative personal characteristics of the analysts. Furthermore, our examination reveals that KPI forecasts issued by industry expert analysts contain more valuable information to the capital market compared to KPI forecasts by non-expert analysts.

We then investigate whether the industry expertise effect on KPI forecasting translates into improved performance in forecasting financial fundamentals. Our results suggest that analyst industry expertise not only enhances EPS forecast accuracy but does so also through a KPI forecasting channel. This finding complements Bradley et al. (2017a) and Givoly et al. (2019). We also explore cross-industry variations to determine how industry expertise affects KPI forecasting in different contexts. Our evidence shows that industry expertise is particularly beneficial in settings characterized by high uncertainty and fast technological changes.

Overall, our study contributes to the literature by offering insights into how analyst industry expertise facilitates forecast performance. We enrich the understanding of the specific mechanism through which analysts leverage their expertise to achieve better forecasting accuracy. Furthermore, by focusing on a primary category of non-financial information—KPIs—we underscore the complementarity of financial and non-financial forecasting, thus complementing the literature on non-financial disclosure.

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**Table 1**
**Sample Selection**

This table outlines the primary steps involved in the sample construction process.

| | KPI Quarterly Forecasts | Analysts | Brokers | KPIs |
|---|---|---|---|---|
| Baseline sample | 17,187,030 | 5,660 | 730 | 163 |
| Actual value released by covered firm | 14,720,688 | 5,549 | 726 | 162 |
| Available forecast publication date | 12,576,810 | 4,848 | 662 | 160 |
| Forecasts released between 2 and 180 days before the actual release date | 4,488,168 | 4,736 | 653 | 160 |
| Latest forecast provided for a specific KPI from a given analyst for a specific company | 1,756,395 | 4,736 | 653 | 160 |
| Non-financial sector | 654,686 | 2,750 | 418 | 120 |
| Industry specific KPIs | 569,772 | 2,224 | 380 | 91 |
| Baseline firm and analyst control variables available | 416,685 | 1,969 | 344 | 89 |
| At least 20 forecasts per KPI and 2 forecasts per KPI-firm-quarter | 381,128 | 1,840 | 323 | 79 |

## Table 2
## Sample Characteristics

This table offers descriptive insights into the sample's characteristics. Panel A presents details on KPI forecasts, firms, and analyst characteristics, categorized by the status of the analyst issuing the forecast (industry expert vs. non-expert). Panel B provides a breakdown of KPI forecast errors by industry, considering the Fama-French 5 industry classifications and the SIC 10 code divisions. Panel C offers a distribution analysis of KPI forecast errors for the 30 most frequently forecasted KPI items, along with their respective reference industries. Panel D showcases the number of forecasted KPI items per analyst-quarter, categorized by Fama-French industry. Panel E reports the percentage of KPI forecasts in each industry issued by industry experts vs. non-expert analysts. Panel F offers a distribution of KPI forecasts issued by expert analysts across different industries.

### Panel A

| | *Industry Expertise = 1* | | | | | | *Industry Expertise = 0* | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **N** | **Mean** | **Std. Dev.** | **p25** | **Median** | **p75** | **N** | **Mean** | **Std. Dev.** | **p25** | **Median** | **p75** | **Diff Mean** | ***p-value*** |
| KPI Forecast Error | 62,975 | 0.101 | 0.248 | 0.007 | 0.027 | 0.080 | 318,153 | 0.169 | 0.364 | 0.009 | 0.037 | 0.135 | -0.068 | *0.000* |
| KPI PMAFE | 62,579 | -0.071 | 0.753 | -0.639 | -0.157 | 0.277 | 315,261 | 0.000 | 0.841 | -0.614 | -0.114 | 0.336 | -0.071 | *0.000* |
| Years Industry Experience | 22,273 | 5.754 | 4.340 | 3.000 | 4.000 | 9.000 | 318,153 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 5.754 | *0.000* |
| Unrelated Industry Expertise | 62,975 | 0.264 | 0.441 | 0.000 | 0.000 | 1.000 | 318,153 | 0.206 | 0.405 | 0.000 | 0.000 | 0.000 | 0.057 | *0.000* |
| Analyst Tenure | 62,975 | 9.301 | 5.119 | 4.929 | 9.197 | 12.970 | 318,153 | 9.339 | 4.918 | 5.403 | 8.986 | 12.830 | -0.038 | *0.077* |
| Analyst Firm Specific Tenure | 62,975 | 4.814 | 4.014 | 1.701 | 3.677 | 6.978 | 318,153 | 4.882 | 3.992 | 1.732 | 3.745 | 7.189 | -0.068 | *0.000* |
| Firms Covered | 62,975 | 19.437 | 10.127 | 14.000 | 19.000 | 23.000 | 318,153 | 21.113 | 12.827 | 15.000 | 19.000 | 25.000 | -1.676 | *0.000* |
| Industries Covered | 62,975 | 4.248 | 3.082 | 2.000 | 3.000 | 6.000 | 318,153 | 3.908 | 2.921 | 2.000 | 3.000 | 5.000 | 0.340 | *0.000* |
| BTM | 62,975 | 2.875 | 4.113 | 1.111 | 1.757 | 3.001 | 318,153 | 3.275 | 4.666 | 1.153 | 1.976 | 3.522 | -0.400 | *0.000* |
| Size | 62,975 | 8.426 | 1.584 | 7.365 | 8.474 | 9.454 | 318,153 | 8.307 | 1.593 | 7.204 | 8.331 | 9.469 | 0.119 | *0.000* |
| Quarter Return | 62,975 | 0.028 | 0.240 | -0.110 | 0.022 | 0.154 | 318,153 | 0.018 | 0.256 | -0.123 | 0.012 | 0.146 | 0.010 | *0.000* |
| Analyst Coverage | 62,975 | 17.853 | 8.406 | 12.000 | 16.000 | 22.000 | 318,153 | 20.513 | 9.391 | 13.000 | 19.000 | 27.000 | -2.660 | *0.000* |
| Forecast Horizon | 62,975 | 47.599 | 41.032 | 14.000 | 30.000 | 85.000 | 318,153 | 48.903 | 41.735 | 14.000 | 32.000 | 85.000 | -1.303 | *0.000* |
| Top Broker Dummy | 62,975 | 0.734 | 0.442 | 0.000 | 1.000 | 1.000 | 318,153 | 0.687 | 0.464 | 0.000 | 1.000 | 1.000 | 0.047 | *0.000* |

**Panel B**

| Fama-French 5 Industries | KPI Forecast Error N | Mean | Std. Dev. | Median |
|---|---|---|---|---|
| Manufacturing, Energy, and Utilities | 202,300 | 0.087 | 0.163 | 0.036 |
| Consumer Durables, Nondurables, Wholesale, Retail, and Some Services | 101,490 | 0.347 | 0.557 | 0.078 |
| Other | 59,997 | 0.076 | 0.188 | 0.024 |
| Business Equipment, Telephone, and Television Transmission | 16,894 | 0.130 | 0.330 | 0.018 |
| Healthcare, Medical Equipment, and Drugs | 447 | 0.839 | 0.741 | 0.588 |

| SIC 10 Industries | KPI Forecast Error N | Mean | Std. Dev. | Median |
|---|---|---|---|---|
| Mining | 213,750 | 0.087 | 0.157 | 0.036 |
| Retail Trade | 96,717 | 0.341 | 0.551 | 0.075 |
| Transportation, Communications, Electric, Gas, and Sanitary Services | 32,995 | 0.095 | 0.272 | 0.014 |
| Construction | 18,393 | 0.056 | 0.082 | 0.032 |
| Services | 9,898 | 0.147 | 0.377 | 0.016 |
| Manufacturing | 4,903 | 0.335 | 0.566 | 0.067 |
| Wholesale Trade | 2,341 | 0.475 | 0.650 | 0.161 |
| Finance, Insurance and Real Estate | 2,049 | 0.021 | 0.040 | 0.010 |
| Agriculture, Forestry and Fishing | 82 | 0.241 | 0.153 | 0.211 |

## Panel C

| KPI | Fama-French 5 Industries | SIC 10 Divisions | KPI Forecast Error | | | |
|---|---|---|---|---|---|---|
| | | | N | Mean | Std. Dev. | Median |
| Production per Day | Manufacturing, Energy, and Utilities | Mining | 55,642 | 0.037 | 0.055 | 0.019 |
| Same Stores Sales - Total | Consumer Durables, Nondurables, Wholesale, Retail, and Some Services | Retail Trade | 45,385 | 0.569 | 0.637 | 0.316 |
| Production per Day - Natural Gas | Manufacturing, Energy, and Utilities | Mining | 32,036 | 0.070 | 0.137 | 0.033 |
| Production per Day - Oil & NGLs | Manufacturing, Energy, and Utilities | Mining | 26,805 | 0.090 | 0.152 | 0.039 |
| Number of Stores at Period End - Total | Consumer Durables, Nondurables, Wholesale, Retail, and Some Services | Retail Trade | 23,908 | 0.027 | 0.083 | 0.004 |
| Realized Price - Natural Gas | Manufacturing, Energy, and Utilities | Mining | 18,863 | 0.146 | 0.171 | 0.089 |
| Realized Price - Oil & NGLs | Manufacturing, Energy, and Utilities | Mining | 18,174 | 0.095 | 0.126 | 0.050 |
| Total Production | Manufacturing, Energy, and Utilities | Mining | 15,565 | 0.048 | 0.070 | 0.026 |
| OPEX Per Unit | Manufacturing, Energy, and Utilities | Mining | 15,043 | 0.237 | 0.300 | 0.123 |
| Production per Day - Oil | Manufacturing, Energy, and Utilities | Mining | 9,850 | 0.067 | 0.129 | 0.028 |
| Cash Cost | Manufacturing, Energy, and Utilities | Mining | 9,228 | 0.130 | 0.218 | 0.069 |
| Selling Space - Total | Consumer Durables, Nondurables, Wholesale, Retail, and Some Services | Retail Trade | 8,162 | 0.042 | 0.086 | 0.008 |
| Same Stores Sales - Domestic | Consumer Durables, Nondurables, Wholesale, Retail, and Some Services | Retail Trade | 7,621 | 0.589 | 0.648 | 0.333 |
| Realized Price | Manufacturing, Energy, and Utilities | Mining | 7,145 | 0.084 | 0.114 | 0.046 |
| Production Per Day - NGLs | Manufacturing, Energy, and Utilities | Mining | 6,891 | 0.105 | 0.224 | 0.058 |
| Net Sales per Square Foot | Consumer Durables, Nondurables, Wholesale, Retail, and Some Services | Retail Trade | 4,409 | 0.205 | 0.361 | 0.046 |
| Number of Subscribers | Business Equipment, Telephone, and Television Transmission | Transportation, Communications, Electric, Gas, and Sanitary Services | 4,327 | 0.030 | 0.060 | 0.008 |
| Number of Stores at Period End - Domestic | Consumer Durables, Nondurables, Wholesale, Retail, and Some Services | Retail Trade | 4,309 | 0.037 | 0.106 | 0.004 |
| Load Factor | Other | Transportation, Communications, Electric, Gas, and Sanitary Services | 4,063 | 0.018 | 0.043 | 0.006 |
| Deliveries Units | Other | Construction | 4,040 | 0.055 | 0.059 | 0.039 |
| New Orders Units | Other | Construction | 3,833 | 0.088 | 0.094 | 0.060 |
| Number Of Stores Opened - Total | Consumer Durables, Nondurables, Wholesale, Retail, and Some Services | Retail Trade | 3,614 | 0.328 | 0.487 | 0.133 |
| Average Revenue Per User | Business Equipment, Telephone, and Television Transmission | Services | 3,600 | 0.038 | 0.065 | 0.016 |
| Available Seat Km | Other | Transportation, Communications, Electric, Gas, and Sanitary Services | 3,399 | 0.018 | 0.054 | 0.003 |
| Backlog Units | Other | Construction | 3,321 | 0.068 | 0.080 | 0.042 |
| Deliveries Average Price | Other | Construction | 3,264 | 0.034 | 0.105 | 0.017 |
| Revenue Passenger Km | Other | Transportation, Communications, Electric, Gas, and Sanitary Services | 3,179 | 0.025 | 0.062 | 0.006 |
| Operating Expenses per ASK | Other | Transportation, Communications, Electric, Gas, and Sanitary Services | 2,880 | 0.049 | 0.094 | 0.016 |
| Passenger Revenue per RPK | Other | Transportation, Communications, Electric, Gas, and Sanitary Services | 2,817 | 0.068 | 0.126 | 0.018 |
| Total Revenue per ASK | Other | Transportation, Communications, Electric, Gas, and Sanitary Services | 2,755 | 0.033 | 0.061 | 0.012 |

## Panel D

| | Number of KPI Forecasts by Analyst-Quarter | | | | | |
|---|---|---|---|---|---|---|
| | *Industry Expertise = 1* | | | *Industry Expertise = 0* | | |
| **Fama-French 5 Industries** | **Mean** | **Std. Dev.** | **Median** | **Mean** | **Std. Dev.** | **Median** |
| Manufacturing, Energy, and Utilities | 3.057 | 2.183 | 3.000 | 3.573 | 2.412 | 3.000 |
| Consumer Durables, Nondurables, Wholesale, Retail, and Some Services | 2.005 | 1.353 | 2.000 | 2.370 | 1.583 | 2.000 |
| Other | 2.601 | 2.223 | 2.000 | 2.592 | 2.273 | 2.000 |
| Business Equipment, Telephone, and Television Transmission | 2.066 | 1.364 | 2.000 | 2.190 | 1.582 | 2.000 |
| Healthcare, Medical Equipment, and Drugs | 1.818 | 0.691 | 2.000 | 1.892 | 0.884 | 2.000 |

## Panel E

| | Percentage of KPI Forecasts Issued by Expert Analyst by Industry | |
|---|---|---|
| | *Industry Expertise = 1* | *Industry Expertise = 10* |
| Manufacturing, Energy, and Utilities | 11.5% | 88.5% |
| Consumer Durables, Nondurables, Wholesale, Retail, and Some Services | 10.9% | 89.1% |
| Other | 45.2% | 54.8% |
| Business Equipment, Telephone, and Television Transmission | 9.4% | 90.6% |
| Healthcare, Medical Equipment, and Drugs | 17.9% | 82.1% |

## Panel F

| | Percentage of KPI Forecasts Issued by Expert Analyst, by Industry of the Expertise | | | | | |
|---|---|---|---|---|---|---|
| | Fama-French 5 Industries | | | | | |
| | Manufacturing, Energy, and Utilities | Consumer Durables, Nondurables, Wholesale, Retail, and Some Services | Other | Business Equipment, Telephone, and Television Transmission | Healthcare, Medical Equipment, and Drugs | Total - Other Industries for which Analyst is Non-Expert |
| Manufacturing, Energy, and Utilities | 84.6% | 10.0% | 5.4% | 0.0% | 0.0% | 15.4% |
| Consumer Durables, Nondurables, Wholesale, Retail, and Some Services | 1.4% | 90.6% | 5.3% | 2.5% | 0.0% | 9.2% |
| Other | 14.6% | 31.9% | 50.1% | 3.3% | 0.2% | 49.9% |
| Business Equipment, Telephone, and Television Transmission | 0.0% | 8.4% | 12.0% | 79.2% | 0.5% | 20.4% |
| Healthcare, Medical Equipment, and Drugs | 0.0% | 25.0% | 37.3% | 0.2% | 37.6% | 62.3% |

## Table 3 – *Industry Expertise and KPI Forecast Error: Main Analysis*

This table explores the impact of industry expertise on KPI forecast errors. Regression results in various columns incorporate distinct fixed effect structures. Standard errors are clustered at both the firm and analyst levels. Significance levels are denoted by *, **, and ***, representing 0.10, 0.05, and 0.01, respectively. Appendix B provides the variable definitions.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | KPI Forecast Error | | | |
| **Industry Expertise** | **-0.078*** ** | **-0.037*** ** | **-0.022*** ** | **-0.042*** ** |
| | **(-19.011)** | **(-4.781)** | **(-3.602)** | **(-3.088)** |
| Analyst Tenure | -0.000 | -0.004 | 0.003 | |
| | (-0.340) | (-0.576) | (1.228) | |
| Analyst Firm Specific Tenure | 0.002*** | 0.000 | 0.001** | 0.000 |
| | (5.119) | (0.951) | (2.074) | (1.592) |
| Firms Covered | -0.003*** | 0.000 | -0.000** | |
| | (-17.733) | (0.463) | (-2.531) | |
| Industries Covered | 0.021*** | -0.001 | -0.000 | |
| | (25.632) | (-0.641) | (-0.447) | |
| BTM | 0.003*** | -0.002*** | | -0.003*** |
| | (8.613) | (-7.320) | | (-7.531) |
| Size | -0.014*** | -0.005*** | | -0.006*** |
| | (-11.881) | (-2.822) | | (-3.225) |
| Quarter Return | -0.006*** | -0.008*** | | -0.005 |
| | (-2.708) | (-2.989) | | (-1.617) |
| Analyst Coverage | -0.001*** | -0.001*** | | -0.001*** |
| | (-4.295) | (-8.964) | | (-4.799) |
| Forecast Horizon | 0.001*** | 0.001*** | 0.001*** | 0.001*** |
| | (25.945) | (38.382) | (39.250) | (33.531) |
| Top Broker Dummy | 0.018*** | -0.006** | -0.001 | -0.015** |
| | (5.949) | (-2.084) | (-0.349) | (-2.466) |
| Fixed Effects | No | Analyst<br>Firm<br>Quarter<br>KPI | Analyst<br>Firm × Quarter<br>KPI | Analyst × Quarter<br>KPI<br>Firm |
| Observations | 381,128 | 380,970 | 380,929 | 377,611 |
| Adjusted R-squared | 0.059 | 0.370 | 0.531 | 0.403 |

**Table 4 – *Industry Expertise and KPI Forecast Error: Identification Analysis***

This table investigates the relationship between industry expertise and KPI forecast errors, utilizing events that result in an exogenous reduction in the proportion of industry expert analysts covering a company. In Column (1), the results are based on a propensity score matched sample where Treatment observations experience a reduction in industry expert coverage due to the closure of brokerage houses. In Column (2), the results are derived from a propensity score matched sample where Treatment observations experience a reduction in industry expert coverage due to the retirement of industry expert analysts. In Column (3), the results are based on the combination of both the brokerage closure and retirement events. Standard errors are clustered at the firm level. Significance levels are denoted by *, **, and ***, representing 0.10, 0.05, and 0.01, respectively. Appendix B provides the variable definitions.

| | (1) | (2) | (3) |
|---|---|---|---|
| | Broker Closure | Analyst Retirement | Broker Closure & Analyst Retirement |
| | | Mean Forecast Error | |
| **Treatment × Post** | **0.058*** | **0.084**** | **0.073**** |
| | **(1.712)** | **(2.038)** | **(2.607)** |
| Post | -0.081** | -0.005 | -0.083*** |
| | (-2.172) | (-0.070) | (-2.799) |
| BTM | -0.001 | 0.002 | -0.000 |
| | (-0.757) | (0.741) | (-0.407) |
| Size | -0.055 | -0.061** | -0.060** |
| | (-0.620) | (-2.263) | (-2.117) |
| Quarter Return | 0.022 | 0.010 | 0.020 |
| | (0.555) | (0.350) | (0.761) |
| Analyst Coverage | -0.002 | -0.001 | -0.002 |
| | (-0.868) | (-0.254) | (-0.989) |
| Constant | 0.670 | 0.688*** | 0.724*** |
| | (1.018) | (3.158) | (3.209) |
| Fixed Effects | Firm<br>Quarter<br>Event | Firm<br>Quarter<br>Event | Firm<br>Quarter<br>Event |
| Observations | 852 | 797 | 1,588 |
| Adjusted R-squared | 0.571 | 0.461 | 0.521 |

**Table 5 – *Industry Expertise and KPI Forecast Error: Robustness Analysis***

This table examines the robustness of the baseline findings regarding the influence of industry expertise on KPI forecast errors. In Panel A, Column (1) introduces an alternative measure of industry expertise based on SIC 10 divisions. Column 2 quantifies industry expertise as a continuous variable, tracking the number of years an analyst has spent in a specific industry. In Column 3, an alternative KPI forecast error measure is considered. In Panel B, Column (1) aggregates observations at the analyst-firm-quarter level. Column (2) aggregates observations at the KPI-firm-quarter level, and in Column (3), observations are aggregated at the KPI-quarter level. In Panel C, Columns (1) and (2) incorporate controls for the analysts' industry experience in fields unrelated to the firm for which a KPI forecast is issued. Columns (3) and (4) introduce controls for the educational background of the analysts and various fixed-effect structures. Standard errors are clustered at both the firm and analyst levels, except for Columns (2) and (3) of Panel B, where they are clustered at the firm level. Significance levels are denoted by *, **, and ***, representing 0.10, 0.05, and 0.01, respectively. Appendix B provides the variable definitions.

**Panel A – *Alternative Measures of Expertise and KPI Forecast Error***

| | (1) | (2) | (3) |
|---|---|---|---|
| | KPI Forecast Error | | KPI PMAFE |
| **Industry Expertise SIC** | **-0.020*** | | |
| | **(-1.799)** | | |
| **Years Industry Experience** | | **-0.009**** | |
| | | **(-2.454)** | |
| **Industry Expertise** | | | **-0.104***** |
| | | | **(-2.634)** |
| Analyst Firm Specific Tenure | 0.000 | 0.000 | 0.003** |
| | (1.566) | (1.370) | (2.470) |
| BTM | -0.003*** | -0.003*** | 0.001 |
| | (-7.523) | (-7.525) | (1.030) |
| Size | -0.006*** | -0.007*** | -0.004 |
| | (-3.218) | (-3.268) | (-0.590) |
| Quarter Return | -0.005 | -0.005 | 0.007 |
| | (-1.617) | (-1.459) | (0.744) |
| Analyst Coverage | -0.001*** | -0.001*** | -0.001 |
| | (-4.800) | (-4.215) | (-0.934) |
| Forecast Horizon | 0.001*** | 0.001*** | 0.004*** |
| | (33.548) | (32.343) | (55.166) |
| Top Broker Dummy | -0.015** | -0.014** | -0.045** |
| | (-2.457) | (-2.128) | (-1.987) |
| Fixed Effects | Analyst × Quarter<br>KPI<br>Firm | Analyst × Quarter<br>KPI<br>Firm | Analyst × Quarter<br>KPI<br>Firm |
| Observations | 377,611 | 337,096 | 374,767 |
| Adjusted R-squared | 0.403 | 0.399 | 0.099 |

**Panel B – *Aggregation of Forecasts***

| | (1) | (2) | (3) |
|---|---|---|---|
| | Analyst-Firm-Quarter | KPI-Firm-Quarter | Firm-Quarter |
| | Mean KPI Forecast Error | | |
| **Industry Expertise** | **-0.049**** | | |
| | **(-2.408)** | | |
| **Proportion Expert Analysts** | | **-0.129***** | **-0.114***** |
| | | **(-12.483)** | **(-7.340)** |
| Analyst Firm Specific Tenure | 0.000 | | |
| | (0.713) | | |
| BTM | -0.004*** | -0.001 | -0.001 |
| | (-6.734) | (-1.587) | (-1.551) |
| Size | -0.008*** | -0.007* | -0.000 |
| | (-2.594) | (-1.648) | (-0.049) |
| Quarter Return | -0.009 | -0.005 | -0.010 |
| | (-1.632) | (-0.804) | (-1.340) |
| Analyst Coverage | -0.001*** | -0.001** | -0.002*** |
| | (-3.889) | (-2.238) | (-2.688) |
| Top Broker Dummy | -0.035*** | | |
| | (-3.132) | | |
| Fixed Effects | Analyst × Quarter<br>Firm | Firm<br>Quarter<br>KPI | Firm<br>Quarter |
| Observations | 131,196 | 70,580 | 20,322 |
| Adjusted R-squared | 0.387 | 0.361 | 0.436 |

## Panel C – *Controlling for Analyst Background*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Unrelated Industry Experience | | Educational Background | |
| | KPI Forecast Error | | | |
| **Industry Expertise** | **-0.054***** | | **-0.032***** | **-0.026***** |
| | **(-3.418)** | | **(-16.472)** | **(-15.444)** |
| **Industry Expertise SIC** | | **-0.029**** | | |
| | | **(-1.997)** | | |
| **Unrelated Industry Expertise** | **-0.046**** | | | |
| | **(-2.129)** | | | |
| **Unrelated Industry Expertise SIC** | | **-0.021** | | |
| | | **(-0.957)** | | |
| **Higher Education** | | | **-0.000** | **0.000** |
| | | | **(-0.146)** | **(0.206)** |
| **Ivy Education** | | | **0.001** | **0.001** |
| | | | **(0.368)** | **(0.313)** |
| Analyst Firm Specific Tenure | 0.000 | 0.000 | -0.000 | 0.000** |
| | (1.597) | (1.574) | (-1.197) | (2.028) |
| BTM | -0.003*** | -0.003*** | 0.000 | |
| | (-7.531) | (-7.526) | (0.533) | |
| Size | -0.006*** | -0.006*** | 0.000*** | |
| | (-3.203) | (-3.215) | (3.229) | |
| Quarter Return | -0.005 | -0.005 | 0.001*** | |
| | (-1.607) | (-1.617) | (3.063) | |
| Analyst Coverage | -0.001*** | -0.001*** | -0.002*** | |
| | (-4.792) | (-4.802) | (-7.452) | |
| Forecast Horizon | 0.001*** | 0.001*** | -0.003 | 0.001*** |
| | (33.520) | (33.536) | (-1.489) | (37.861) |
| Top Broker Dummy | -0.015** | -0.015** | -0.008*** | 0.001 |
| | (-2.425) | (-2.433) | (-2.861) | (0.392) |
| Analyst Tenure | | | -0.001*** | -0.000** |
| | | | (-8.419) | (-2.028) |
| Firms Covered | | | 0.001*** | 0.000 |
| | | | (37.755) | (0.976) |
| Industries Covered | | | -0.001 | 0.001*** |
| | | | (-0.527) | (2.767) |
| Fixed Effects | Analyst × Quarter<br>KPI<br>Firm | Analyst × Quarter<br>KPI<br>Firm | Firm<br>Quarter<br>KPI | Firm × Quarter<br>KPI |
| Observations | 377,611 | 377,611 | 352,587 | 352,002 |
| Adjusted R-squared | 0.403 | 0.403 | 0.362 | 0.523 |

**Table 6 – *Industry Expertise and KPI Forecast Error: Cross-Sectional Analysis***

This table delves into the influence of industry expertise on KPI forecast errors within the cross-section. We segment the sample based on the characteristics of the industry where the covered firm operates. In Column (1), the sample is divided according to industry-level uncertainty, which we calculate as the average sales volatility of firms within an industry over the 16 quarters leading up to a given quarter (De Franco et al., 2023). In Column (2), the sample is categorized based on the technology intensity of the industry, calculated as the quarterly average ratio of *R&D Expenses* to *Total Sales* in the industry where a firm operates. In Column (3), we partition the sample based on industry-level reporting complexity, which we gauge as the quarterly average *Accounting Reporting Complexity* of the industry where the company operates (Hoitash and Hoitash, 2018). Standard errors are clustered at both the firm and analyst levels. Significance levels are denoted by *, **, and ***, representing 0.10, 0.05, and 0.01, respectively. Appendix B provides the variable definitions.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Industry Uncertainty | | Technological Change | | Reporting Complexity | |
| | High | Low | High | Low | High | Low |
| **Industry Expertise** | **-0.070**** | **-0.018***** | **-0.076***** | **-0.003** | **-0.060***** | **-0.031** |
| | **(-2.456)** | **(-3.282)** | **(-3.157)** | **(-0.252)** | **(-2.959)** | **(-0.918)** |
| Analyst Tenure | 0.001 | 0.000 | 0.000 | 0.001* | 0.001* | 0.001 |
| | (1.285) | (1.291) | (0.572) | (1.739) | (1.884) | (1.545) |
| BTM | -0.004*** | 0.000 | -0.002*** | -0.003*** | -0.002*** | -0.003*** |
| | (-7.448) | (0.603) | (-5.325) | (-6.552) | (-3.743) | (-7.271) |
| Size | 0.026*** | -0.010*** | -0.000 | -0.010*** | -0.004 | -0.009*** |
| | (2.728) | (-6.832) | (-0.099) | (-3.767) | (-1.282) | (-4.203) |
| Quarter Return | -0.017* | -0.000 | 0.004 | -0.007* | -0.009 | -0.001 |
| | (-1.903) | (-0.060) | (0.960) | (-1.648) | (-1.573) | (-0.326) |
| Analyst Coverage | -0.003*** | -0.000** | 0.000 | -0.001*** | -0.001*** | -0.001*** |
| | (-4.780) | (-2.065) | (0.466) | (-5.278) | (-3.263) | (-3.318) |
| Forecast Horizon | 0.001*** | 0.000*** | 0.001*** | 0.001*** | 0.001*** | 0.001*** |
| | (25.989) | (26.119) | (18.047) | (28.885) | (20.605) | (29.402) |
| Top Broker Dummy | -0.027 | -0.013*** | -0.016 | -0.014** | -0.025** | -0.010 |
| | (-1.501) | (-3.607) | (-1.260) | (-2.012) | (-2.316) | (-1.359) |
| Fixed Effects | Analyst × Quarter<br>KPI<br>Firm | | Analyst × Quarter<br>KPI<br>Firm | | Analyst × Quarter<br>KPI<br>Firm | |
| F-test *p-value* | *0.071* | | *0.000* | | *0.235* | |
| Observations | 125,562 | 251,637 | 119,094 | 257,241 | 124,834 | 251,650 |
| Adjusted R-squared | 0.351 | 0.322 | 0.470 | 0.397 | 0.441 | 0.396 |

## Table 7 – *KPIs Categories*

This table provides information on the most commonly forecasted KPIs, including their classification, description, and corresponding frequencies. Monetary KPIs are reported in Panel A and gauge the predicted monetary value of revenues (*Revenue per unit*) or costs (*Cost per unit*) per unit of output/input generated/used by a firm. Volume KPIs, reported in Panel B, include measures of resources put into a process, such as capital and labor, serving as precursors to performance (*Inputs*) or metrics quantifying the volume of products or services a company is projected to successfully deliver to its customers (*Outputs*).

### Panel A – Monetary KPIs

| KPI | Type | Description | N |
|---|---|---|---|
| Same Stores Sales - Total | Revenue per unit | The sales from retail stores that have been open for at least a year. | 45,385 |
| Realized Price - Natural Gas | Revenue per unit | The average price at which a company sells its natural gas. | 18,863 |
| Realized Price - Oil & NGLs | Revenue per unit | The average price at which a company sells its oil and natural gas liquids (NGLs). | 18,174 |
| OPEX per Unit | Cost per unit | The average operational expenditure incurred per unit of product in the energy sector. | 15,043 |
| Cash Cost | Cost per unit | The average cash cost incurred in producing a unit of product in the energy sector. | 9,228 |
| Same Stores Sales - Domestic | Revenue per unit | The sales from retail domestic stores that have been open for at least a year. | 7,621 |
| Realized Price | Revenue per unit | The average price at which a product is sold in the energy sector. | 7,145 |
| Net sales per square foot | Revenue per unit | The amount of revenues generated per unit of retail store's space. | 4,409 |
| Average Revenue Per User | Revenue per unit | The average revenue generated per user in the services sector. | 3,600 |
| Deliveries Average Price | Revenue per unit | The average price of units delivered in the construction sector. | 3,264 |
| Operating Expenses per ASK | Cost per unit | The average operating cost an airline incurs for each available seat kilometer. | 2,880 |
| Passenger revenue per RPK | Revenue per unit | The average revenue an airline makes for flying one passenger for one kilometer. | 2,817 |
| Total Revenue per ASK | Revenue per unit | The total revenue earned by the airline per available seat kilometer. | 2,755 |
| Backlog Average Price | Revenue per unit | The average price of units in the backlog in the construction sector. | 2,362 |
| Passenger revenue per ASK | Revenue per unit | The average revenue an airline makes for each available seat kilometer. | 2,122 |

### Panel B – Volume and Capacity KPIs

| KPI | Type | Description | N |
|---|---|---|---|
| Production per day | Output | The amount of production (oil/gas) a company produces per day. | 55,642 |
| Production per day - Natural Gas | Output | The amount of natural gas a company produces per day. | 32,036 |
| Production per day - Oil & NGLs | Output | The amount of oil and natural gas liquids (NGLs) a company produces per day. | 26,805 |
| Number of Stores at Period End - Total | Inputs | The total number of stores that a retailer has at the end of a specific period. | 23,908 |
| Total Production | Output | The volume of oil/gas extracted in a given period in the energy sector. | 15,565 |
| Production Per Day - Oil | Output | The amount of oil a company produces per day. | 9,850 |
| Selling Space - Total | Inputs | The total amount of floor space available for selling goods/services in a group of stores. | 8,162 |
| Production Per Day - NGLs | Output | The amount of natural gas liquids (NGLs) a company produces per day. | 6,891 |
| Number of Subscribers | Output | The total number of active subscribers or users of a service. | 4,327 |
| Number of Stores at Period End - Domestic | Inputs | The number of domestic stores that a retailer has at the end of a specific period. | 4,309 |
| Load Factor | Output | The percentage of available seating capacity that is filled with passengers. | 4,063 |
| Deliveries Units | Output | The number of units delivered to customers in the construction sector. | 4,040 |
| New Orders Units | Output | The number of new orders received in the construction sector. | 3,833 |
| Number of Stores Opened - Total | Inputs | The total number of new stores that a retailer has opened in a specific period. | 3,614 |
| Available seat km | Inputs | The number of seats available times the distance flown for an airline. | 3,399 |

**Table 8 – *KPIs Categories and Industry Expertise in Forecasting KPIs***

This table investigates the relative forecasting capabilities of industry expert analysts across different KPI categories. In Panel A, Column (1), we compare monetary KPIs with volume KPIs. In Column (2), we extend our analysis to explore more detailed subcategories of KPIs. In Panel B, we assess the comparative performance of industry expert and non-expert analysts across the entire range of KPIs (Columns (1) and (2)), monetary KPIs (Columns (3) and (4)), and volume KPIs (Columns (5) and (6)), during periods with or without inflation shocks. Standard errors are clustered at both the firm and analyst levels. Significance levels are denoted by *, **, and ***, representing 0.10, 0.05, and 0.01, respectively. Appendix B provides the variable definitions.

**Panel A – *KPI Categories***

| | (1) | (2) |
|---|---|---|
| | Forecast Error | |
| **Industry Expertise × Monetary KPI** | **-0.024*** | |
| | **(-1.833)** | |
| **Industry Expertise × Cost per Unit KPI** | | **-0.080***** |
| | | **(-5.420)** |
| **Industry Expertise × Revenue per Unit KPI** | | **-0.067***** |
| | | **(-4.600)** |
| **Industry Expertise × Output KPI** | | **-0.046***** |
| | | **(-3.364)** |
| **Industry Expertise × Input KPI** | | **0.023** |
| | | **(1.358)** |
| **Industry Expertise** | **-0.044***** | |
| | **(-9.518)** | |
| Analyst Tenure | 0.000* | 0.000* |
| | (1.665) | (1.690) |
| BTM | -0.003*** | -0.003*** |
| | (-7.544) | (-7.560) |
| Size | -0.006*** | -0.006*** |
| | (-3.253) | (-3.283) |
| Quarter Return | -0.005 | -0.005 |
| | (-1.613) | (-1.590) |
| Analyst Coverage | -0.001*** | -0.001*** |
| | (-4.790) | (-4.797) |
| Forecast Horizon | 0.001*** | 0.001*** |
| | (33.457) | (33.402) |
| Top Broker Dummy | -0.015** | -0.015** |
| | (-2.449) | (-2.439) |
| Fixed Effects | Analyst × Quarter<br>KPI<br>Firm | Analyst × Quarter<br>KPI<br>Firm |
| Observations | 377,611 | 377,515 |
| Adjusted R-squared | 0.403 | 0.403 |

**Panel B – *Inflation Shocks***

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | All KPIs | | Monetary KPIs | | Volume KPIs | |
| | High | Low | High | Low | High | Low |
| **Industry Expertise** | **-0.056*** ** | **-0.026*** | **-0.105*** ** | **-0.013** | **-0.031*** ** | **-0.018** ** |
| | **(-3.231)** | **(-1.733)** | **(-2.705)** | **(-0.355)** | **(-3.696)** | **(-2.107)** |
| Analyst Tenure | 0.000 | 0.001** | -0.001 | 0.002** | 0.000* | 0.000 |
| | (0.199) | (2.464) | (-0.751) | (2.155) | (1.696) | (1.179) |
| BTM | -0.003*** | -0.002*** | -0.007*** | -0.003*** | -0.000 | -0.001** |
| | (-7.374) | (-4.357) | (-8.733) | (-3.938) | (-0.023) | (-2.485) |
| Size | -0.005** | -0.006*** | 0.008 | 0.003 | -0.012*** | -0.013*** |
| | (-2.169) | (-2.734) | (1.337) | (0.606) | (-6.815) | (-7.380) |
| Quarter Return | -0.004 | -0.006 | -0.010 | -0.020** | -0.003 | 0.001 |
| | (-0.909) | (-1.421) | (-0.884) | (-2.034) | (-1.082) | (0.164) |
| Analyst Coverage | -0.000** | -0.001*** | -0.000 | -0.003*** | -0.001*** | -0.000 |
| | (-1.971) | (-5.620) | (-0.647) | (-5.689) | (-3.596) | (-1.286) |
| Forecast Horizon | 0.001*** | 0.001*** | 0.001*** | 0.001*** | 0.000*** | 0.000*** |
| | (24.954) | (27.227) | (21.079) | (22.222) | (13.571) | (17.174) |
| Top Broker Dummy | -0.021** | -0.012 | -0.044* | -0.004 | -0.011* | -0.011*** |
| | (-2.274) | (-1.457) | (-1.848) | (-0.186) | (-1.889) | (-2.639) |
| Fixed Effects | Analyst × Quarter<br>KPI<br>Firm | | Analyst × Quarter<br>KPI<br>Firm | | Analyst × Quarter<br>KPI<br>Firm | |
| F-test *p-value* | *0.098* | | *0.032* | | *0.170* | |
| Observations | 187,630 | 189,949 | 73,233 | 77,486 | 112,890 | 110,983 |
| Adjusted R-squared | 0.416 | 0.402 | 0.391 | 0.385 | 0.421 | 0.426 |

## Table 9 – *Connecting KPI and EPS Forecast Accuracy*

This table presents the findings from a path analysis investigating the relationship between analyst industry expertise, KPI forecast error, and EPS forecast error. The direct path illustrates the immediate impact of analyst industry expertise on EPS forecast error, while the mediated path demonstrates how analyst industry expertise influences EPS forecast error through its effect on KPI forecast error. A visual representation of this analysis is provided in Figure 3. Standard errors are robust to potential heteroscedasticity. Significance levels are denoted by *, **, and ***, representing 0.10, 0.05, and 0.01, respectively. Appendix B provides the variable definitions.

| | (1) |
|---|---|
| | EPS Forecast Error |
| | Mediating variable: KPI Forecast Error |
| **Direct Effect** | |
| P (Industry Expertise, EPS Forecast Error) | -0.036* |
| | (-1.680) |
| **Mediated Effect** | |
| P (Industry Expertise, KPI Forecast Error) | -0.073*** |
| | (-4.630) |
| P (KPI Forecast Error, EPS Forecast Error) | 0.090*** |
| | (14.180) |
| P (Industry Expertise, KPI Forecast Error) × P (KPI Forecast Error, EPS Forecast Error) | -0.007*** |
| | (4.380) |
| Time Varying Controls | Yes |
| Fixed Effects | Analyst × Quarter<br>Firm |
| Observations | 114,574 |

**Table 10 – *Market Reaction to Industry Expert Forecast Revisions***

This table presents regression analyses that investigate the market response to KPI forecast revisions. The dependent variable captures cumulative abnormal stock returns within a 3-day window surrounding these revisions. In Columns (1) and (2), we analyze observations at the KPI revision level, while in Columns (3) and (4), the data is aggregated at the analyst-firm-date level. Each regression controls for the concurrent EPS forecast revision issued by the analysts. Standard errors are clustered at both the firm and analyst levels. Significance levels are denoted by *, **, and ***, representing 0.10, 0.05, and 0.01, respectively. Appendix B provides the variable definitions.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | KPI Revision | | Analyst-Firm-Date Aggregated Revision | |
| | Full Sample | Excluding EA Dates | Full Sample | Excluding EA Dates |
| **Industry Expertise × Signed KPI Revision** | **0.420*** ** | **0.452** ** | **0.541** ** | **0.770*** ** |
| | **(2.751)** | **(2.403)** | **(2.226)** | **(2.920)** |
| Signed KPI Revision | 1.837*** | 1.208*** | 2.787*** | 1.818*** |
| | (31.289) | (17.469) | (26.276) | (14.549) |
| Industry Expertise | 0.129 | -0.137 | 0.125 | 0.029 |
| | (0.412) | (-0.346) | (0.447) | (0.083) |
| EPS Revision | 0.861*** | 0.147* | 2.157*** | 0.674*** |
| | (11.677) | (1.699) | (23.053) | (6.578) |
| Analyst Firm Specific Tenure | 0.011 | 0.015 | 0.012* | 0.015* |
| | (1.368) | (1.456) | (1.858) | (1.856) |
| BTM | 0.023*** | 0.007 | 0.017*** | 0.005 |
| | (3.835) | (1.209) | (2.680) | (0.560) |
| Size | -0.298*** | -0.365*** | -0.157** | -0.197** |
| | (-3.961) | (-4.092) | (-2.030) | (-2.283) |
| Quarter Return | 2.304*** | 0.550*** | 4.381*** | 0.814*** |
| | (26.302) | (5.947) | (25.793) | (4.632) |
| Analyst Coverage | -0.036*** | -0.015** | -0.021*** | -0.009 |
| | (-6.714) | (-2.493) | (-3.534) | (-1.416) |
| Top Broker Dummy | 0.037 | 0.151 | 0.112 | 0.440 |
| | (0.214) | (0.748) | (0.356) | (1.017) |
| Fixed Effects | Analyst × Quarter<br>KPI<br>Firm | Analyst × Quarter<br>KPI<br>Firm | Analyst × Quarter<br>Firm | Analyst × Quarter<br>Firm |
| Observations | 1,571,717 | 1,071,944 | 154,671 | 93,891 |
| Adjusted R-squared | 0.043 | 0.045 | 0.059 | 0.037 |

**Figure 1**

This figure illustrates the estimated treatment effects (with 95% confidence intervals) on the Treated × Post interactions for each quarter over a three-year period surrounding an exogenous loss of coverage of industry expert analysts (Broker Closure & Analyst Retirement). Coefficients are derived based on quarterly treatment effects relative to the benchmark quarter when the shock occurs. The dependent variable captures the average KPI Forecast Error at the firm-quarter level.

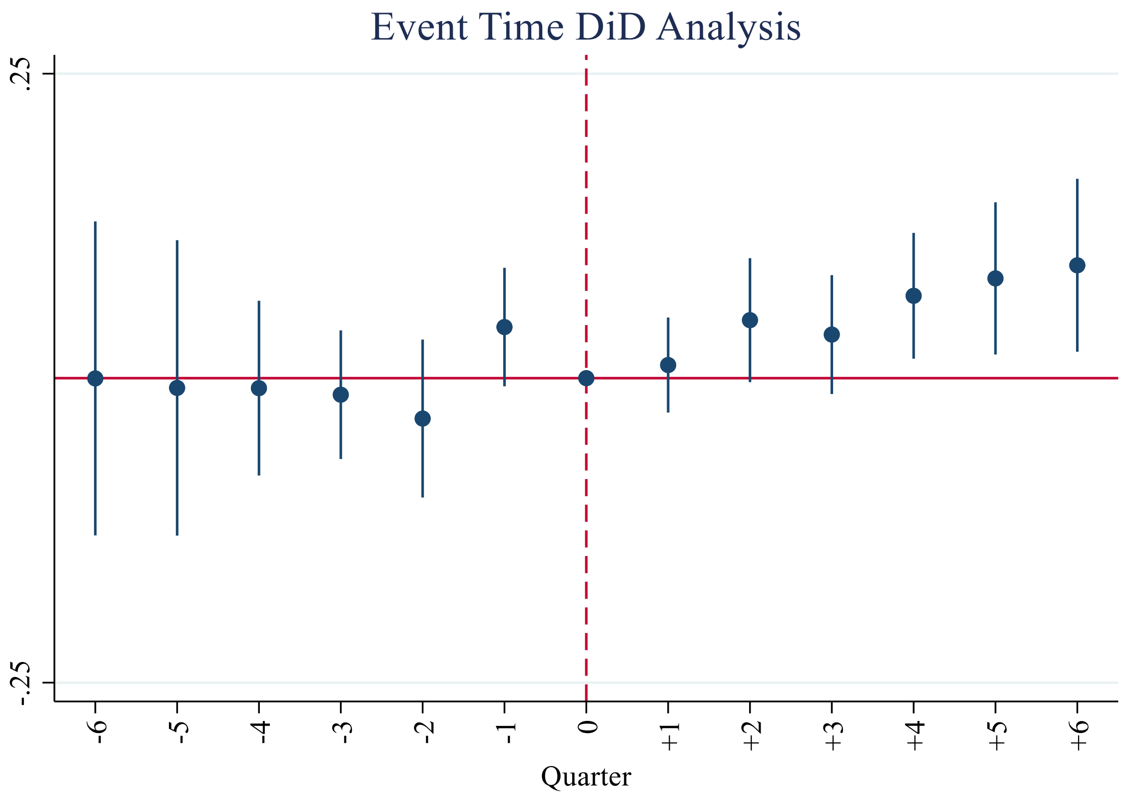


**Figure 2**

This figure plots the relationship between the average KPI forecast error and the years of industry experience of the analyst.

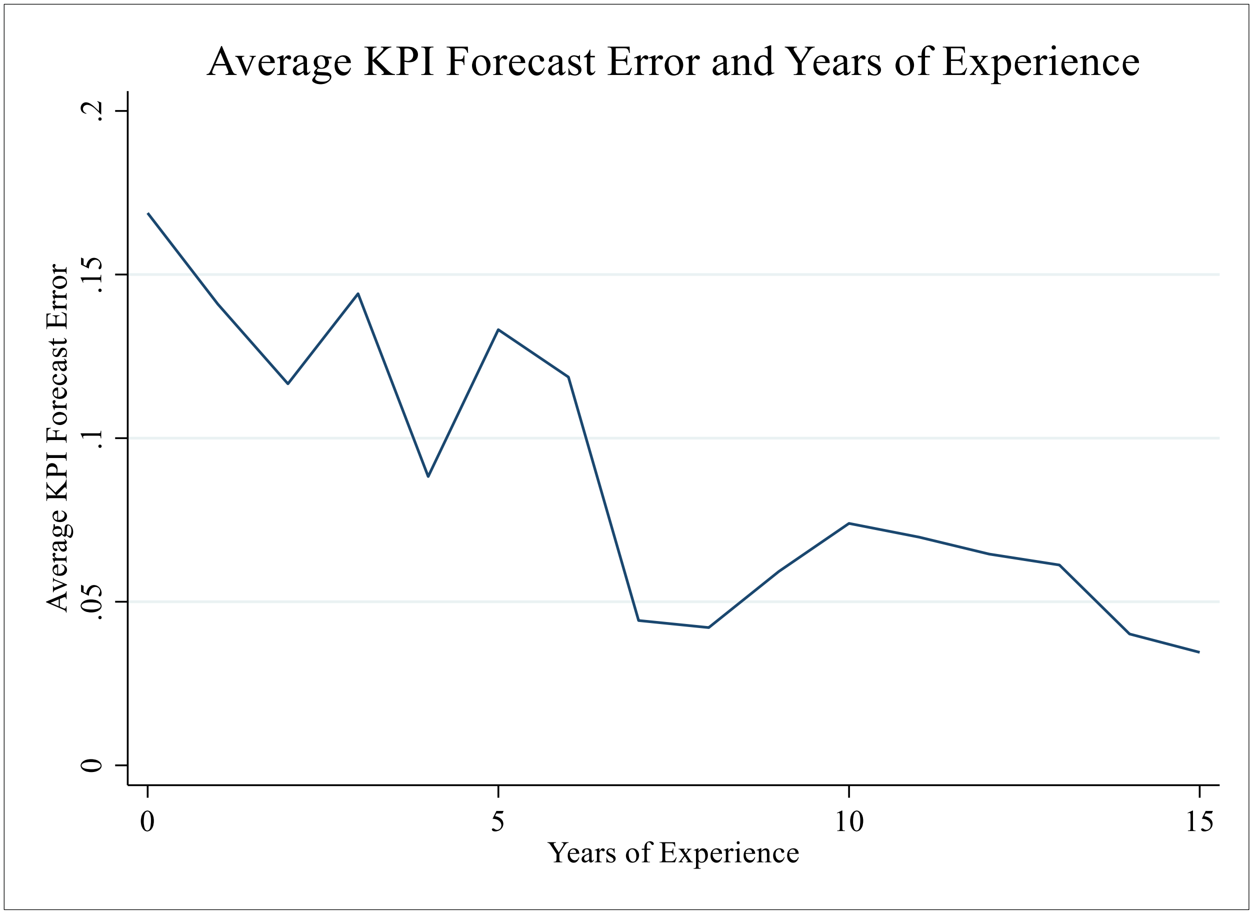
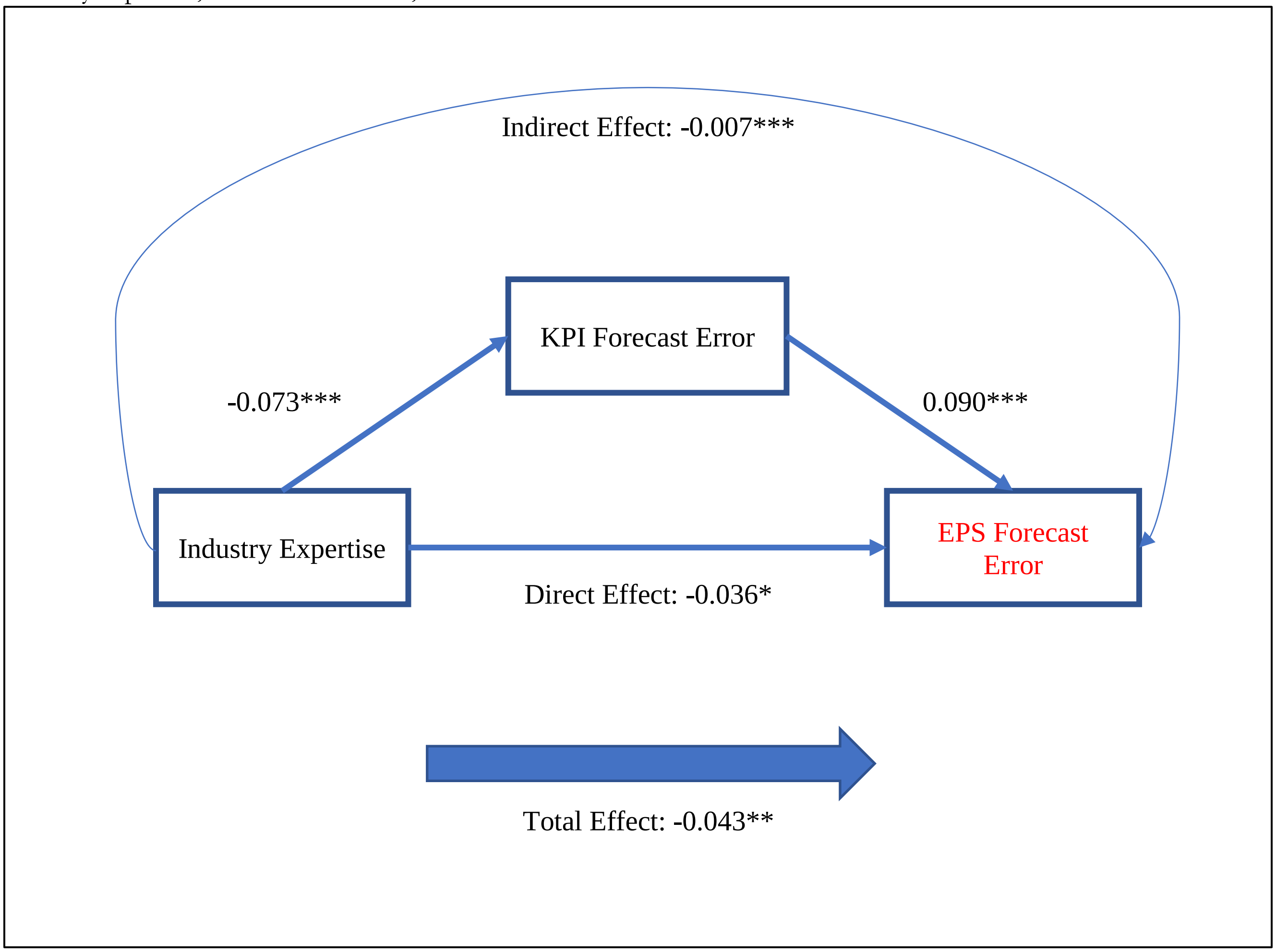


**Figure 3**

This figure provides a visual representation of the path analysis investigating the relationship between analyst industry expertise, KPI forecast error, and EPS forecast error.



## Appendix A – *KPI Items in the Final Sample*

| | |
|---|---|
| Access Lines | Number of Subscribers |
| Annual Subscription Value (ASV) | Occupancy Rate - Domestic |
| Available seat km (ASK) | Occupancy Rate - International |
| Average Revenue Per User (ARPU) | Occupancy Rate - Total |
| Backlog Average Price | Operating Expenses per ASK |
| Backlog Units | Operating Expenses per ASK excluding. |
| Brent Price | OPEX per Unit |
| Cancellation Rate | Paid Net Adds |
| Cash Cost | Passenger revenue per ASK |
| Churn | Passenger revenue per RPK |
| Contribution Profit | Production per day |
| Cost per Gross Add | Production per day - Natural Gas |
| Daily Active Users | Production Per Day - NGLs |
| Daily Room Rate (ADR) - Domestic | Production Per Day - Oil |
| Daily Room Rate (ADR) - International | Production per day - Oil & NGLs |
| Daily Room Rate (ADR) - Total | Realized Price |
| Deliveries Average Price | Realized Price - Gas & NGLs |
| Deliveries Units | Realized Price - Natural Gas |
| Edmonton Par Oil Price | Realized Price - Oil & NGLs |
| Gross Adds | Revenue passenger |
| Load Factor | Revenue passenger km (RPKs) |
| Marijuana | Revenue per Available Room - Domestic |
| Medical Cost Ratio | Revenue per Available Room - International |
| Monthly Active Users | Revenue per Available Room - Total |
| Monthly Revenue Per User | Revenue Per Unit |
| Monthly Unique Users | Same Store Adjusted Admissions |
| Net Adds | Same Store Admissions |
| Net sales per square foot | Same Store Revenue per Adjusted Admissions |
| New Orders Average Price | Same Stores Sales - Domestic |
| New Orders Units | Same Stores Sales - International |
| New Student Enrollment | Same Stores Sales - Total |
| Number of Stores at Period End - Domestic | Selling Space - Domestic |
| Number of Stores at Period End - International | Selling Space - International |
| Number of Stores at Period End - Total | Selling Space - Total |
| Number of Stores Closed - Domestic | Subscriber Acquisition Cost |
| Number of Stores Closed - Total | Total Production |
| Number of Stores Opened - Domestic | Total Revenue per ASK |
| Number of Stores Opened - International | Total Student Enrollment |
| Number of Stores Opened - Total | Volume Growth |
| Number of Stores Relocated - Total | |

## Appendix B – *Variable Definitions*

| Variable | Definition |
|---|---|
| **Analyst Coverage** | Number of analysts covering a firm in a given quarter. |
| **Analyst Firm Specific Tenure** | Duration in years that an analyst has provided forecasts for a specific firm. |
| **Analyst Tenure** | The length of time an individual has been an equity analyst. |
| **BTM** | The book-to-market ratio of the firm. |
| **Firm Size** | The logarithm of the total assets of the firm. |
| **Firms Covered** | Number of firms an analyst covers in a given quarter. |
| **Forecast Horizon** | Number of days between the analyst's forecast and the actual release date of the KPI. |
| **Industries Covered** | Number of industries an analyst covers in a given quarter. |
| **Industry Expertise** | Indicator variable taking the value of one if the analyst worked in the same industry as the firm he covers. Based on Fama-French 5 industry sectors. |
| **Industry Expertise SIC** | Indicator variable taking the value of one if the analyst worked in the same industry as the firm he covers. Based on SIC the 10 major industry sectors. |
| **KPI Forecast Error** | The KPI forecast error, computed as in Givoly et al. (2017). |
| **Quarterly Return** | Buy-and-hold stock return minus the equal-weighted market return during the 90 days leading up to the forecast. |
| **KPI PMAFE** | The KPI proportional mean absolute forecast error. |
| **Top Broker Dummy** | Binary variable indicating whether the analyst is affiliated with a top decile brokerage house. |
| **Unrelated Industry Expertise** | Indicator variable takes the value of one if the analyst has pre-analyst work experience in an industry different from that of the firm he covers. Based on the Fama-French 5 industry sectors. |
| **Unrelated Industry Expertise SIC** | Indicator variable takes the value of one if the analyst has pre-analyst work experience in an industry different from that of the firm he covers. Based on SIC the 10 major industry sectors. |
| **Years Industry Experience** | The number of years an analyst worked in the same industry as the firm he covers. |