Consensus?
An Examination of Differences in Earnings Information Across Forecast Data Providers

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Abstract

We compare the earnings information produced by the five largest forecast data providers (FDPs) – Bloomberg, Capital IQ, FactSet, I/B/E/S, and Zacks – and observe substantial differences across FDPs in both forecasted and actual street earnings values, and thus the earnings surprise, for the same firm-quarter. We provide evidence that differences in the earnings surprise across FDPs for the same firm-quarter (hereafter, "FDP differences") have implications for the efficiency of the price response to earnings, equity market liquidity, and volatility. We also find that, when faced with material FDP differences, investors rely more heavily upon earnings information with higher expected quality and salience. On average, relative to the other FDPs, I/B/E/S ranks highly in our measures of quality and salience and investors rely more heavily upon its earnings information, validating its use as a representative FDP in academic research. Taken together, our results are consistent with FDPs pursuing differentiated information production strategies that generate capital market frictions in situations when these strategies lead to material FDP differences.

"Today, the reality of earnings has been completely subsumed by what I've come to think of as the madness of the consensus estimate. ***This one number****–which, as I'm sure you know, is the average earnings estimate of all the sell-side analysts who cover a particular company, and is compiled by a handful of firms like IBES…–now utterly dominates life on Wall Street."* – Joseph Nocera, *Money* magazine, June 1998 [emphasis added]

1. Introduction

I/B/E/S, a prominent forecast data provider (FDP), claims to have created the consensus earnings estimate industry in 1972 (I/B/E/S [2000]). Consistent with the above quote from Nocera [1998], prior research finds that the "street" earnings information produced by FDPs such as I/B/E/S "displaced GAAP earnings as a primary determinant of stock prices" in the early 1990s (Bradshaw and Sloan [2002], 41). Since then, the global financial data industry has continued to grow in breadth and scope to $35 billion in annual revenues as of 2021, split among several major providers (Burton-Taylor [2021]). We seek to provide the first large-sample investigation of whether the earnings information produced by the five largest FDPs – Bloomberg, Capital IQ, FactSet, I/B/E/S, and Zacks – differs across FDPs for the same firm-quarter and whether such differences are associated with capital market consequences.

In a three-part framework, we investigate the extent to which FDPs adopt product differentiation strategies when competing to satisfy investors' demand for earnings information. First, we examine the prevalence and magnitude of differences in the earnings surprise produced across FDPs for the same firm-quarter (hereafter, "FDP differences"). Second, we examine whether FDP differences materially impact market responsiveness, liquidity, and volatility around earnings announcements. Third, we posit that FDPs compete on both the quality and salience of the earnings information they produce and examine whether investors rely more heavily on a given FDP's earnings information when that information is of higher quality or more salient.

We focus on the FDP-reported earnings surprise, which results from two of the most prominent services performed by FDPs: aggregating sell-side analysts' individual earnings forecasts into a "consensus" forecast, and providing a measure of actual, realized street earnings.[1] We expect that the competitive equilibrium in the FDP industry determines the degree of product differentiation across FDPs. To the extent that earnings information is a standardized commodity, the FDP industry should tend towards perfect competition, such that FDPs compete primarily on price, and competitive forces eliminate material differences across FDPs. However, to the extent that consumers have heterogenous preferences regarding the quality, cost, and other characteristics of FDP-produced earnings information, or if FDPs make differential investments in product quality, then the product market for earnings information may exhibit material and systematic differentiation across FDPs (e.g., Porter [1980], Shaked and Sutton [1987]). For example, some FDPs may place a greater emphasis on data quality, while others may maximize the breadth of their data collection efforts or focus on minimizing subscription costs.

Consistent with a market structure tending more towards perfect competition, early studies found few differences in earnings information across FDPs during the 1980s and 1990s (Philbrick and Ricks [1991], Abarbanell and Lehavy [2002]). However, we expect that FDPs' information production has likely changed over time and has shifted towards product differentiation. Such a shift is consistent with changes in the competitive landscape of modern data-driven capital markets, as research documents that the number of data items disseminated by FDPs has soared in recent decades (Givoly et al. [2019], Hand et al. [2022]). Anecdotally, market participants have reported noticeable differences in earnings information across FDPs in recent years. In particular, the *Wall Street Journal* reports that earnings information "is likely to vary from one provider to the next" and that "trying to reconcile the numbers can get confusing" (McGinty [2015]).

[1]Analysts often exclude line items from their forecasts that they deem to be less value relevant. The street earnings provided by FDPs are generally reported on the same "consensus" accounting basis as the forecasts gathered by the FDP. Accordingly, consensus estimates and street earnings provided by FDPs often differ from generally accepted accounting principles (GAAP). Black et al. [2018] review the non-GAAP literature.

To analyze our research questions, we form a sample of firm-quarters using earnings forecasts and street earnings from Bloomberg, Capital IQ, FactSet, I/B/E/S, and Zacks. We begin by comparing the breadth and intensity of coverage for 209,035 firm-quarters in CRSP and Compustat from 2002 to 2017 and observe substantial variation in the number of firms covered by and the number of analyst-contributors to these five FDPs over time. In particular, 96 percent of these firm-quarters are covered by at least one FDP, while 46 percent are covered by all five FDPs.

Focusing on firm-quarters covered by all five FDPs, we observe consensus earnings per share (EPS) forecasts that differ across FDPs in 50 percent of firm-quarters and street EPS that differ across FDPs in 37 percent of firm-quarters.[2] These differences in forecasted and/or street EPS lead to FDP differences in the earnings surprise for 57 percent of firm-quarters. The magnitude of the difference exceeds \$0.05 per share over 45 percent of the time. Moreover, in approximately 9 percent of firm-quarters, we find that at least one FDP indicates that the firm missed expectations while at least one other FDP indicates that the firm beat expectations. We then examine the determinants of FDP differences and find that the magnitude of FDP differences is larger for firm-quarters where FDPs are more likely to differ in their contributor bases or accounting methodologies, as well as for firm-quarters that exhibit greater earnings uncertainty as captured by I/B/E/S analyst dispersion, I/B/E/S processing timeliness, and other firm-quarter characteristics associated with earnings uncertainty. Overall, the prevalence and economic magnitude of FDP differences suggests that FDPs adopt differentiated product market strategies.

We then assess whether FDP differences are material. We predict that FDP differences make it more difficult for investors to integrate the implications of the earnings announcement into their trading decisions, leading to market frictions. We test and find that the magnitude of FDP

[2] We focus on EPS differences of more than \$0.015 to ensure that the differences are not due to rounding differences.

differences is negatively associated with the speed of the price response to quarterly earnings news, announcement-window liquidity, and volatility. For example, *ceteris paribus*, market reaction timeliness is 2.42 percent lower, relative to the sample mean, for firm-quarters where at least one FDP indicates the firm missed while at least one FDP indicates the firm beat expectations.

The prevalence and materiality of FDP differences suggests that FDPs adopt differentiated product market strategies to satisfy investors' demand for earnings information and, in turn, investors may rely on some FDPs' earnings information more than others. This can be described as FDPs *moderating* investors' response to earnings news (Jollineau and Bowen [2023]). We thus compare earnings response coefficients across the five FDPs for the same firm-quarter. We focus on I/B/E/S as a representative FDP as it is the most commonly used FDP in academic research as well as the FDP with the broadest coverage throughout our sample period (I/B/E/S [2000]).[3] We find that, on average, the market response associated with the earnings surprises produced by Zacks, Bloomberg, and FactSet is significantly weaker than, while the market response associated with the Capital IQ earnings surprise does not significantly differ from, that of I/B/E/S.

To explain *why* investors rely on some FDPs' earnings information more than others, we develop a conceptual model in which investors rely more heavily on a given FDP's earnings information when that information is either of higher quality or more salient among investors. In other words, we predict that quality and salience *mediate* the moderating effect of FDPs on investors' earnings response. Accordingly, we implement a structural equation modeling (SEM) approach developed by Kwan and Chan [2018] to estimate mediated moderation effects.[4] Within

[3] Some research, including Mikhail et al. [1997], uses Zacks data, while other research, such as Cheng et al. [2021] and Hand et al. [2022], uses FactSet.

[4] While "mediated moderation" and "moderated mediation" differ conceptually, prior accounting literature focuses on the latter because traditional empirical methods are not able to differentially model these concepts (Jollineau and Bowen [2023]). To our knowledge, ours is the first accounting study to apply Kwan and Chan's [2018] method, which may be a useful tool to future research examining hypotheses that involve mediated moderation.

each firm-quarter, we rank the FDPs based on seven proxies for the quality and salience of each FDP's earnings information, including their historical firm-specific accuracy, how well their street earnings have historically predicted the firm's future performance, and the extent to which their earnings information is cited by the media during the earnings announcement window.

We find that, on average, I/B/E/S ranks highly across our seven measures of relative quality and salience, consistent with its stronger on-average earnings response relative to the other FDPs. Moreover, our measures of quality and salience largely explain (i.e., mediate) the on-average differences in earnings response coefficients across FDPs. For example, our results suggest that Zacks' lower relative accuracy accounts for approximately 52.2 percent of its weaker on-average investor response relative to I/B/E/S, while its smaller analyst following and fewer media citations also represent significant indirect effects. Overall, our empirical results support our conceptual model and are consistent with FDPs competing for customers by making differential investments in the quality and salience of the earnings information they produce.[5]

Our study contributes to the burgeoning literature on the role of FDPs in capital markets (e.g., Akbas et al. [2018], Schaub [2018], Kaplan et al. [2021], Bochkay et al. [2022]). This literature demonstrates that FDPs serve as important information intermediaries in modern capital markets, but largely relies on evidence from I/B/E/S following the assumption that I/B/E/S is a representative FDP. This assumption has remained untested following early research that found few differences across FDPs during the 1980s and 1990s (Philbrick and Ricks [1991], Abarbanell and Lehavy [2002]). In a more recent sample, we find that there are often material differences in the earnings information produced by I/B/E/S and other prominent FDPs which increase investors'

[5] We acknowledge that FDPs likely compete along additional dimensions that we cannot systematically observe, such as subscription costs and dissemination timeliness. Nevertheless, our results suggest that quality and salience contribute significantly towards explaining the competitive forces that shape FDPs' information production strategies.

costs of processing earnings information. These observed differences reflect variation in the quality and salience of their earnings information, consistent with FDPs pursuing differentiated product market strategies. Thus, our study contributes to our understanding of the broader FDP industry and its competitive landscape.[6]

Our study also validates the common use of I/B/E/S earnings information in academic research. Although we observe variation in how I/B/E/S performs relative to other FDPs across firms and over time, our analyses suggest that, on average, the market response to earnings aligns well with the I/B/E/S earnings surprise, and that I/B/E/S earnings information ranks highly in our measures of quality and salience.

Finally, our study has implications for market participants – including sell-side analysts, buy-side institutional investors, retail investors, and journalists – who rely on FDPs to assess firm performance, value stocks, and implement investment strategies. While articles in the financial press have increased awareness of anecdotal FDP differences (e.g., McGinty [2015]), we provide the first large-sample evidence on the prevalence, magnitude, and implications of *within firm-quarter* FDP differences for the five largest FDPs. We also show that differences in the expected quality and salience of an FDP's information can help market participants understand when a given FDP's information is likely to be more or less useful and/or influential among investors.

2. *Background and Motivation*

2.1. PRIOR LITERATURE

Beginning with Ball and Brown [1968], a large body of research finds that stock returns are associated with earnings innovations (i.e., "news") relative to investor expectations. While early studies examined earnings news based on reported GAAP earnings, Bradshaw and Sloan

[6] Relatedly, our study contributes to an emerging literature about the data economy (Easterwood [2024]).

[2002, 45] document the rise of the consensus earnings surprise during the 1990s, noting that "the concepts of consensus earnings and earnings surprise relative to consensus are relatively new, and were not pervasive on Wall Street until the early 1990s."[7]

Market participants' increased focus on non-GAAP earnings since the 1990s has given rise to a large academic literature examining the causes and consequences of non-GAAP earnings, as well as the roles of managers, analysts, and FDPs in the use of non-GAAP earnings (Black et al. [2018]). In this regard, Bradshaw and Sloan ([2002], 44) note that "[FDPs] act as the arbiters of the magnitude of earnings surprises and appear to be increasingly following the lead of management and analysts in excluding ever more charges from earnings." Around this time, several early studies examine differences between various FDP consensus-based earnings measures and GAAP earnings (from Compustat) (Philbrick and Ricks [1991], Abarbanell and Lehavy [2002, 2007]). Abarbanell and Lehavy [2002] conclude that I/B/E/S, Zacks, and First Call apply similar formulae for excluding items from reported earnings and proceed to focus on differences between I/B/E/S and GAAP earnings. In other words, these early studies viewed street earnings as a commoditized product and focused on GAAP versus street differences.

Recent research examines FDP information processing methods and the role of FDPs as intermediaries in capital markets. These studies largely focus on I/B/E/S as a representative FDP. Brown and Larocque [2013] find that I/B/E/S street earnings often differ from the earnings used by individual analysts. Akbas et al. [2018] show that information processing delays in the dissemination of I/B/E/S forecast revisions are associated with a delayed market response. Kaplan et al. [2021] find that I/B/E/S exercises discretion in excluding optimistic forecasts from its

[7] Additional studies document that FDP consensus forecasts represent the market's earnings expectations (e.g., Fried and Givoly [1982], Schipper [1991]), and that market participants generally follow FDP-produced street earnings (e.g., Bradshaw and Sloan [2002], Brown and Sivakumar [2003], Bradshaw et al. [2018]).

consensus. Bochkay et al. [2022] leverage an exogenous change in I/B/E/S methodology to show that FDPs' methodological choices affect the predictive value of street earnings, as well as analysts' and investors' reliance on I/B/E/S street earnings. Ljungqvist et al. [2009] and Call et al. [2021] demonstrate that ex-post changes in I/B/E/S historical data (i.e., "rewriting history") can affect research inferences.

2.2. INSTITUTIONAL BACKGROUND

The focus on I/B/E/S in prior research overlooks the other large FDPs. While I/B/E/S initiated the consensus earnings estimate industry in the early 1970s, competition in the FDP industry has grown over time. Zacks was the second major FDP to produce consensus earnings information and claims to be the first FDP to have distributed *quarterly* consensus earnings forecasts in the early 1980s (Zacks [2011]).[8] More recently, IPREO [2018, 1] reports:

> "Today, there are four major consensus providers (FactSet, Thomson Reuters, Bloomberg, S&P Capital IQ), rather than one. None of the 'Big 4' have dominant market share or voice, and each are as likely as the other to be cited as the 'headline number' on news feeds… Nowadays, each corporate needs to monitor not one, but four, major consensus providers; each provider calculates their own consensus, often based on a different analyst set, and with different methodologies."

Accordingly, we study the earnings information of Bloomberg, Capital IQ, FactSet, and I/B/E/S, the four primary players in the FDP industry, as well as Zacks which has significant current and historical market share.[9] Each of these FDPs collects forecasts from sell-side financial analysts, aggregates them into a consensus forecast, and produces a corresponding actual performance

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[8] First Call competed in this space until 2000 when it was integrated into I/B/E/S. Throughout our sample period, I/B/E/S was owned by Thomson Reuters, but was spun off as part of Refinitiv in 2018 and is now owned by LSEG.

[9] Our focus on these five FDPs excludes crowd-sourced earnings forecasts available via newer platforms such as Estimize, which have less coverage both across time and firms. While we expect the inferences from our study to generalize to other FDPs, the implications of product differentiation by smaller FDPs may not be as material.

metric (i.e., street earnings) once a firm reports its earnings for the period. These forecasts and street earnings are provided (for a fee) to market participants as well as academic researchers.[10,11]

The individual forecasts included in a given FDP's "consensus" forecast can vary due to the contractual sourcing agreements with the independent research shops and sell-side brokerages that produce earnings forecasts. Each FDP can also exercise discretion over which contributed forecasts to include in its consensus (Kaplan et al. [2021]). Moreover, FDP forecasts and street earnings need not follow GAAP, and each FDP has discretion over the accounting methods governing both the consensus forecast and corresponding street earnings value.

During our sample period, each of Bloomberg, Capital IQ, FactSet, and I/B/E/S determine street earnings using an accounting basis that reflects the earnings items that the majority of their contributing analysts were including in their forecasts (i.e., the majority basis), while Zacks uses an "adjust and include" methodology that adjusts both forecasted and reported earnings to a standardized Zacks "before non-recurring items" (BNRI) measurement basis. In some cases, reported earnings can include "unexpected" line items for which the majority treatment is unknown ex-ante, and FDPs must determine how to account for these unexpected items in street earnings (Bochkay et al. [2022]). This aspect of FDPs' methodologies can result in material differences across FDPs' *street earnings*, even when the FDPs produce the same consensus *forecast*. Appendix A summarizes the five FDPs' processes for collecting forecasts and forming street earnings.

[10] Sell-side brokerages both contribute and subscribe to FDP data. Many large institutional investors use information provided by FDPs. Bloomberg terminals – which provide much more than earnings information – are an essential tool for many trading desks. Zacks subscriptions are available *within* the Bloomberg terminal, alongside Bloomberg's own consensus estimates. In addition, FactSet is used by Fidelity while BlackRock accesses analyst research via Refinitiv. Our conversations with FDP staff indicate that major investment funds often subscribe to more than one FDP.

[11] According to a 2021 Burton-Taylor International Consulting report, a Bloomberg terminal subscription costs $27,660 per year and discounts are available for additional terminals. A FactSet subscription costs $12,000 per year while Refinitiv Eikon costs $22,00 per year, with a stripped-down version available for as little as $3,600 per year. Capital IQ pricing is not published publicly; their product offerings tend to be customized. Zacks offers several levels of subscriptions ranging from $249 to $2,995 per year. (Sources: www.wallstreetprep.com and www.zacks.com.)

Anecdotally, instances of material FDP differences have been documented in recent years. For example, when Box.com announced earnings for Q4 2015, its CEO attributed the unexpected market response to confusion among FDPs over the appropriate share count for EPS, claiming that "while the correct number showed up in FactSet, it didn't in Thomson Reuters" (Lipton [2015]). While market participants are aware that earnings measures can vary across FDPs (e.g., McGinty [2015]), the prevalence, magnitude, and implications of FDP differences remain unknown.

2.3. DETERMINANTS AND CONSEQUENCES OF FDP DIFFERENCES

We expect that competitive forces in the FDP industry determine the degree of variation in the earnings information produced across FDPs. Porter's [1980] *Competitive Strategy* contrasts cost leadership and product differentiation as two opposing ends of the competitive spectrum for a given industry. In the context of the FDP industry, if investors view earnings information as a commodity, then FDPs are likely to focus primarily on cost leadership, with few differences in the quality and features of the earnings information they produce. This appears consistent with early studies' findings of few material differences across FDPs at a time when the industry was relatively consolidated and focused on developing the market for consensus earnings estimates (Philbrick and Ricks [1991], Abarbanell and Lehavy [2002]). On the other end of the competitive spectrum, FDPs can attempt to differentiate their earnings information either vertically (e.g., in terms of quality) or horizontally (e.g., in terms of unique feature combinations that cater to investors' individual and heterogenous preferences) (Shaked and Sutton [1987]).

Recent academic and anecdotal evidence suggest that competition across FDPs has likely shifted towards product differentiation in recent decades. For example, Hand et al. [2022] document that the number of data items tracked by FDPs has climbed since 2001 and differs across I/B/E/S and FactSet, demonstrating differentiation in FDPs' breadth of product offerings. As noted above, the business press has also documented anecdotal evidence of FDP differences (e.g., McGinty [2015]). Accordingly, we expect that FDPs compete with one another across multiple dimensions. For example, some FDPs may invest more heavily in quality control versus breadth of data items supplied. Similarly, some FDPs may invest in deeper (narrower) relationships with a targeted (broader) set of contributing analysts/brokers. Moreover, FDPs vary in the services they offer and the quality and ease of use of their user interface (Coleman and Dyer [2023]).

Thus, we begin our study by examining the prevalence, magnitude, and determinants of FDP differences. We predict that FDP differences are a joint function of FDPs' product differentiation strategies and underlying earnings uncertainty. For example, differences in contributing analysts can lead to differences in the consensus forecasts across FDPs, but such differences are more likely to manifest in quarters where a firm's underlying earnings are more uncertain and individual analysts exhibit greater dispersion in their earnings forecasts. Similarly, FDPs can adopt different accounting methods, and these accounting methods are more likely to lead to FDP differences in quarters when firms report transitory or unexpected earnings items.

While product differentiation strategies allow FDPs to innovate and compete to better satisfy investors' demand for earnings information, the resulting FDP differences may also be associated with capital market consequences. As noted by McGinty [2015], FDP differences may be "confusing." Thus, FDP differences may be associated with increased information processing costs, as investors are forced to integrate multiple earnings news signals into their trading decisions to reach a consensus on the new equilibrium price. Accordingly, following Blankespoor et al. [2020], we test whether greater FDP differences are associated with reductions in announcement-window liquidity, volatility, and the efficiency of the price response to earnings.

To the extent that our first two sets of analyses provide evidence of market-relevant FDP differences, it becomes important to better understand the dynamics of *how* FDPs compete with one another to satisfy investors' demand for information. Accordingly, in Section 5, we develop a conceptual model in which FDPs compete to attract investors to their products by differentiating the quality and salience of their earnings information, and we test whether investors behave in a manner consistent with our model. Specifically, we examine whether investors rely on some FDPs' earnings information more than others and if this differential reliance is attributable to differences in the quality and salience of the FDPs' earnings information.

3. *Data, Sample, and Prevalence of FDP Differences*

3.1. SAMPLE SELECTION

Table 1, Panel A summarizes our sample selection procedures. We begin with 209,035 firm-quarters from 2002 to 2017 from the Compustat-CRSP merged file (hereafter, the "CCM Dataset"). Our sample period begins in 2002 as this is the first year of broad data availability for FactSet (Hand et al. [2022], Figure 1), and ends in the third quarter of 2017 because this is our final quarter of access to Capital IQ data. We then merge in the mean EPS forecast, street EPS, and number of analysts included in the consensus for each of the five forecast data providers. Appendix B provides details on how we downloaded and/or hand-collected forecasts and street earnings from each of the five FDPs. I/B/E/S – the FDP most used in prior analyst research (Call et al. [2021]) – covers 185,045 firm-quarters from the CCM dataset. We observe coverage by all five FDPs for 96,070 of these firm-quarters. We focus on the 80,196 firm-quarters with available data to form our variables of interest. We then truncate the sample at the first and ninety-ninth percentiles based on the values of street earnings and earnings surprise for each of the five FDPs, resulting in a final sample of 75,723 firm-quarters (i.e., 378,615 FDP-firm-quarter observations).[12]

In Table 1, Panel B and Figure 1, we provide details of the coverage of the firm-quarters contained in the CCM dataset by each FDP. Given that we eliminate small and thinly-traded (i.e., below $1 share price) firms, the majority of firm-quarters in the CCM dataset are covered by at least one FDP. In particular, of the 209,035 firm-quarters in the CCM dataset, 201,541 (i.e., 96.41%) are covered by at least one of the five FDPs and 96,070 (i.e., 45.96%) are covered by all five FDPs. As shown in Figure 1, I/B/E/S covers the highest percentage of firm-quarters, beginning at 79.82 percent of firm-quarters in 2002 and reaching 91.20 percent in 2017. Zacks also offers consistently broad coverage throughout our sample period, while the remaining FDPs exhibit significant growth in coverage over our sample period.[13]

Figure 2 plots the average number of contributing analysts per firm-quarter by FDP for our final sample of 75,723 firm-quarters.[14] The average number of contributing analysts appears similar for I/B/E/S and Capital IQ for much of our sample period, and for Bloomberg, Capital IQ, FactSet, and I/B/E/S from 2009 onwards. We also note a decline in the number of contributing analysts in Zacks since 2009, which we surmise is driven by Zacks' methodology change in 2008 to include stock-based compensation expense (SBC) as a recurring item in street earnings.

While information about each FDP's market share based on their number of customers is proprietary and unobservable to researchers, we consider how often the name of each FDP is cited

[12] We truncate (rather than winsorize) based on street earnings and earnings surprise in order to preserve the FDP values for a given firm-quarter, as winsorizing an extreme value may artificially induce differences across FDPs.
[13] As we note in Appendix B, given the difficulty in finding historical data for since-acquired or delisted firms in Bloomberg, our estimate of Bloomberg coverage is likely downward-biased.
[14] We cannot observe the identities of the individual analysts contributing to each FDP's consensus forecast and, thus, cannot determine the overlap with which individual analysts contribute to the five FDPs. Moreover, we cannot use the FDPs' detail files to re-create the consensus forecasts. The detail files are subject to entitlements not applicable to the consensus files, which restrict the ability to view all analysts following the firm in each quarter (Call et al. [2021]).

by the media over time to provide more context regarding the changing landscape of the FDP industry and the relative importance of each FDP within the industry. Specifically, in Figure 3, we summarize the number of news articles in Lexis-Uni that cite the name of each FDP related to earnings from 2000 to 2020. As shown in Figure 3a, I/B/E/S is the most cited FDP, and these citations have increased exponentially in recent years. These findings suggest that market participants are well aware of I/B/E/S' earnings information and that I/B/E/S has become increasingly popular over time. Further, as shown in Figure 3b, there has been considerable growth in the number of citations of Capital IQ, Zacks, and Bloomberg over time. Finally, Figure 3b highlights that FactSet received relatively few media citations until 2011 but has received approximately 6,000 cites per year since 2011.

3.2. PREVALENCE OF DIFFERENCES ACROSS FORECAST DATA PROVIDERS

Next, we summarize the differences (of \$0.015 or more) across FDPs in street and forecasted EPS and the earnings surprise in Figure 4. We observe the same street (forecasted) EPS across all five FDPs for 63.02 (50.33) percent of the firm-quarters in our sample, and two, three, four, and five different street (forecasted) EPS figures for 29.35, 6.28, 1.17, and 0.18 (35.76, 11.01, 2.49, and 0.42) percent of firm-quarters, respectively. Finally, we observe the same earnings surprise across all five FDPs for 43.24 percent of the firm-quarters in our sample, two different earnings surprises for 36.12 percent of firm-quarters, and three, four, and five different earnings surprises for 14.57, 4.86, and 1.21 percent of firm-quarters, respectively.

Figure 5 provides descriptive statistics on the economic magnitudes of the differences we examine. For firm-quarters in our sample that exhibit differences across FDPs, each column of Figure 5 provides the percentage of firm-quarters where the difference between the maximum and minimum value of each measure (i.e., street EPS, forecasted EPS, or earnings surprise) falls within the range specified below that column. Notably, only 12.93, 26.72, and 24.76 percent of our observed differences in actuals, forecasts, and surprises, respectively, represent relatively minor differences of \$0.015 to \$0.02 cents per share, while 34.63, 19.26, and 22.70 percent of firm-quarters contain differences between FDPs greater than ten cents per share. Overall, these descriptive statistics suggest that the differences across FDPs are economically meaningful.

3.3. DETERMINANTS OF FDP DIFFERENCES

As discussed in Section 2.3, we expect that FDP differences are a joint function of FDPs' product differentiation strategies and underlying firm-quarter earnings uncertainty. Accordingly, we model the determinants of FDP differences using the following OLS regression:

$$\begin{aligned} Diff_{jt} &= A \times FDP\ Methodology\ Differences_{jt} + \\ &B \times FDP\ and\ Analyst\ Uncertainty_{jt} + C \times Other\ Firm\text{-}Quarter\ Characteristics_{jt} \\ &+ D \times YearQTRFE_t + \varepsilon_{jt} \end{aligned} \tag{1}$$

In Equation (1), the unit of observation is the firm-quarter for firm *j* ending in quarter *t*. *Diff* represents one of three measures of the magnitude of FDP differences – *Max Less Min Surp*, *Std Dev Surp*, and *Miss and Beat*. *Max Less Min Surp* is the difference between the maximum and minimum value of FDP earnings surprises (shown in Figure 5), scaled by the stock price and multiplied by 100. *Std Dev Surp* is the standard deviation of FDP earnings surprises, scaled by price, and multiplied by 100. *Miss and Beat* is an indicator variable that equals one if at least one FDP's earnings surprise is less than -\$0.015 and at least one is greater than \$0.015. We model *Diff* as a function of three vectors of explanatory variables (*FDP Methodology Differences, FDP and Analyst Uncertainty,* and *Other Firm-Quarter Characteristics*), and include year-quarter fixed effects (*YearQTR FE*), identifying firm-quarters ending in calendar quarter *t*, to control for any time trends in the magnitude of FDP differences unrelated to the other determinants in the model.

FDP Methodology Differences is a vector of six variables related to differences in FDPs' methodologies. It includes *Unique Following,* the number of unique analyst following counts across the five FDPs for firm *j* in quarter *t,* because differences in the contributing analyst pools across FDPs can generate differences in the consensus forecast, and, to a lesser degree, may affect the street earnings majority accounting basis. *SBC High*, an indicator variable that equals one if SBC expense is above the quarterly sample median, captures a unique feature of Zacks' "before non-recurring items" (BNRI) accounting basis. Zacks uniformly *includes* SBC in its BNRI basis, whereas other FDPs exclude SBC when the majority of analysts exclude it for a given firm-quarter.[15] We include *Unexpected Item*, which identifies firm-quarters reporting earnings items that were not expected by analysts prior to the earnings announcement, as Bochkay et al. [2022] demonstrate that FDPs have discretion over their methodology for excluding these items from street earnings. More generally, FDPs are more likely to differ in their treatment of special items compared to common items such as revenues and cost of goods sold, so we also include *abs(Special Items)*. Finally, as discussed in Section 2, FDPs can differ in the share counts used in the denominator of their EPS measures. Accordingly, we include two variables, *abs(ΔShares),* and *Stock Split*, to capture when FDPs are more likely to differ in their EPS denominator.

FDP and Analyst Uncertainty includes extant measures of analysts' and FDPs' underlying firm-quarter uncertainty. Given that prior studies commonly employ I/B/E/S analysts' dispersion as a proxy for firm-quarter uncertainty, we include the standard deviation of I/B/E/S analysts' EPS forecasts for the firm-quarter (*Dispersion*). Following Akbas et al. [2018], who find that I/B/E/S

[15] Results in Tables 3 and 4 are robust to excluding one FDP at a time, suggesting that no single FDP drives our results. As Zacks follows a different methodology relative to the other four FDPs for defining street EPS, we present the analyses in Tables 3 and 4 where we exclude Zacks in the internet appendix (see Tables IA.1 and IA.2).

activation delay is associated with earnings uncertainty, we also include the lag from the earnings press release time until the street value is activated in I/B/E/S (*Activation Delay*).

Finally, we include *Other Firm-Quarter Characteristics* that may be associated with firm-quarter uncertainty, and, in turn, FDP differences. This vector of variables includes size (*MVE*); book-to-market ratio (*BTM*); institutional ownership (*Inst Own*); whether the firm issued guidance (*Guidance*); the absolute value of the percentage change in income before extraordinary items (*abs(ΔIB)*); the standard deviation of daily stock returns (*Ret Vol*); and an indicator variable equal to one if quarter *t* is the fourth fiscal quarter (*Q4*).

While we group our determinants into three categories to highlight our primary motivation for each measure, these categories are not mutually exclusive. For example, although we include *Unexpected Item* in *FDP Methodology Differences*, unexpected items revealed at the earnings announcement may also enhance FDP and analyst uncertainty. Formal variable definitions for all variables are provided in Appendix C. We winsorize all independent variables at the first and ninety-ninth percentile. For ease of interpretation, when estimating all regressions, we standardize all continuous independent variables to have a mean of zero and a standard deviation of one.

Table 2 provides descriptive statistics for the variables used in our firm-quarter analyses. Consistent with the magnitudes of differences shown in Figure 5, *Max Less Min Surp* has a mean (median) of 0.174 (0.047), and *Std Dev Surp* has a mean (median) of 0.090 (0.031). Notably, the mean of *Miss and Beat* indicates that for 9.1 percent of firm-quarters, FDPs disagree as to whether the firm beat or missed expectations. *Unique Following* has a mean (median) of 3.089 (3.000), suggesting there are differences in the contributing analyst pools across FDPs. Lastly, the descriptive statistics suggest our sample exhibits significant variation in earnings components. For example, *abs(Special Items)* has a mean (median) of 0.336 (0.002), while the mean of *Unexpected Item* indicates that 42.5 percent of firm-quarters report a large, unexpected item.

Table 3 presents the results of estimating Equation (1). We find that all three of our proxies for the magnitude of FDP differences are increasing in both FDPs' methodology differences and underlying earnings uncertainty. For instance, each FDP difference measure is positively associated with the number of unique analysts following counts contributing to the consensus forecast across FDPs, high levels of SBC, the existence of an unexpected item revealed at the earnings announcement, the magnitude of special items reported in the quarter, and the change in shares outstanding. In economic terms, we find a one-standard deviation increase in the unique analysts contributing to the consensus forecast, leads to a 9.77 (8.89) percent increase in *Max Less Min* (*Std Dev Surp*) relative to the sample mean, consistent with differences in the contributing analyst pools across FDPs resulting in significant FDP differences.[16] FDP differences are also positively associated with the two extant I/B/E/S-based measures of FDP and analyst uncertainty: dispersion and activation delay of street earnings. Lastly, with respect to the other firm-quarter characteristics, we find that FDP differences are negatively associated with firm size and more prevalent when the quarter is the firm's fourth fiscal quarter.[17]

Taken together, the results in Table 3 suggest that FDP differences are non-random and vary systematically with the FDPs' methodology differences and underlying earnings uncertainty. We therefore include the explanatory variables from Equation (1) as control variables in subsequent tests. However, we note that the adjusted R-squared values in Table 3 range from 0.040

[16] 9.77% = 0.017 / 0.174, where 0.017 is the coefficient estimate on *Unique Following* in column (1), and 0.174 is the sample mean of *Max Less Min Surp*.

[17] In untabulated analyses, we examine the differences in FDPs' consensus forecasts and street earnings. For both, differences are associated with proxies for FDP methodology differences and FDP and analyst uncertainty, including *Unique Following*, *SBC High*, *Unexpected Item*, *abs(Special Items)*, *abs(∆Shares)*, *Dispersion*, and *Activation Delay*.

to 0.284, suggesting that much of the variation in FDP differences is not simply explained by previously identified aspects of firm-quarter earnings uncertainty.

4. Market Consequences of FDP Differences

We next examine whether FDP differences are associated with the market's response to earnings information as FDP differences may confuse investors (McGinty [2015]) or increase their disclosure processing costs (Blankespoor et al. [2020]). In particular, when investors collectively observe multiple earnings surprise values, it may be more difficult for investors to integrate the earnings news into their valuation models or to reach a consensus on the new equilibrium price.

We examine three market outcomes that prior research has shown are impaired when investors face higher processing costs, namely price responsiveness, abnormal volatility, and liquidity. In particular, theoretical work on disclosure processing costs suggests higher processing costs reduce the price responsiveness to disclosure, resulting in slower price reactions (Grossman and Stiglitz [1980], Verrecchia [1982], Sims [2003], [2010]). In addition, processing costs reduce investors' use of the information in disclosure. Therefore, as abnormal volatility around a disclosure reflects investors' use of the disclosure to revise their beliefs, Blankespoor et al. [2020] find that processing costs are negatively associated with abnormal price volatility. Finally, as described in Blankespoor et al. [2020], decreased use of disclosure leads to less informed investors (Kyle [1989]), which in turn decreases competition among informed traders and motivates less trading, reducing liquidity (Avdis and Banerjee [2019]). Overall, we expect that if FDP differences increase investors' costs of processing earnings information, then when these differences are larger, price responsiveness, abnormal volatility, and liquidity will be reduced. We examine whether FDP differences are associated with these market outcomes by estimating the following OLS regression:

$$Market\ Outcome_{jt} = \beta_1\ Diff_{jt} + B \times Controls_{jt} + YearQTR_t\ FE + Firm_j\ FE + \varepsilon_{jt} \qquad (2)$$

For market outcomes in Equation (2), we use *MRT* to reflect market reaction timeliness, *Abnormal Volatility* to reflect abnormal volatility, and *Abnormal Spread*, *Abnormal Depth*, or *Abnormal Price Impact* to reflect liquidity.[18] We measure *MRT* over the 32 trading-hours following the earnings announcement.[19] We measure *Abnormal Volatility*, *Abnormal Spread*, *Abnormal Depth*, and *Abnormal Price Impact* following Blankespoor et al. [2020] over the two trading days beginning on the earnings announcement date. *Abnormal Spread* and *Abnormal Price Impact* (*Abnormal Depth*) are decreasing (increasing) in liquidity.

Our independent variable of interest, *Diff*, is again one of three measures of FDP differences. *Controls* includes the independent variables from Equation (1) as well the absolute value of the earnings surprise scaled by price (*abs(Surprise)*), as our dependent measures likely vary with the magnitude of the earnings surprise.[20] We include year-quarter fixed effects and firm fixed effects (*FirmFE*).

In Panel A of Table 4, we present results for the estimation of Equation (2), when *MRT* is the dependent variable. We find that market reaction timeliness is negatively associated with all three measures of the magnitude of FDP differences. In economic terms, a within-fixed-effect one standard deviation increase in *Max Less Min Surp* (*Std Dev Surp*) is associated with a 0.74 (0.89) percent decrease in *MRT*, relative to the sample mean.[21] Moreover, when at least one FDP indicates the firm missed earnings expectations and at least one FDP indicates the firm beat earnings

[18] Our sample for these analyses begins in 2004, the first full calendar year with TAQ millisecond data available.
[19] We winsorize each return fraction at -1 and 1 to reduce the influence of small denominators and extreme reactions.
[20] We calculate *abs(Surprise)* using I/B/E/S earnings information consistent with prior research. However, (untabulated) results are qualitatively similar if we use the average earnings surprise across the five FDPs.
[21] -0.74% = (-0.481 × 0.282) / 18.457, where -0.481 is the coefficient estimate on *Max Less Min Surp* in column (1), 0.282 is the within-fixed-effect sample standard deviation of *Max Less Min Surp* (untabulated), and 18.457 is the sample mean of *MRT*. We calculate the standard deviation of variables within fixed-effects groups using the sumhdfe Stata package (available from: https://github.com/ed-dehaan/sumhdfe).

expectations for the same quarter, it is associated with a 2.42 percent decrease in *MRT*, relative to the sample mean.

In Panel B of Table 4, we find *Abnormal Volatility* is negatively associated with all three measures of FDP differences, suggesting that FDP differences impede investors' use of earnings information. A within-fixed-effect one standard deviation increase in *Max Less Min Surp* (*Std Dev Surp*) is associated with a 1.46 (1.54) percent decrease in *Abnormal Volatility*, relative to the sample mean. When at least one FDP indicates the firm missed earnings expectations and one FDP indicates the firm beat earnings expectations for the same quarter, it is associated with a 1.79 percent decrease in *Abnormal Volatility*, relative to the sample mean.

Finally, in Panel C of Table 4 we use three measures of liquidity as the dependent variable. We find that two of the three measures of liquidity (i.e., *Abnormal Depth* and *Abnormal Price Impact*) are negatively associated with the magnitude of FDP differences. In economic terms, a within-fixed-effect one standard deviation increase in *Max Less Min Surp* (*Std Dev Surp*) is associated with an 8.32 (9.29) percent decrease in *Abnormal Depth* and a 0.46 (0.44) percent increase in *Abnormal Price Impact*, relative to the sample mean. When at least one FDP indicates the firm missed earnings expectations and one FDP indicates the firm beat earnings expectations for the same quarter, we observe a 17.33 (1.13) percent decrease (increase) in *Abnormal Depth* (*Abnormal Price Impact*), relative to the sample mean. Overall, the results in Table 4 suggest that FDP differences increase investors' costs of processing earnings information, resulting in a reduction in the market's informational efficiency. Moreover, these results suggest that FDP differences are likely to be incremental to extant I/B/E/S-based measures of analyst and FDP uncertainty in their association with the efficiency of the market's response to earnings information, consistent with FDP differences representing an additional dimension of earnings-related uncertainty or confusion that is novel to those identified in prior research.[22]

5. *Examining the Competitive Forces that Shape FDPs' Earnings Information*

5.1. CONCEPTUAL MODEL

The results thus far indicate that FDP differences are both prevalent and material. This suggests that the FDP industry's competitive equilibrium fosters meaningful product differentiation across FDPs' earnings information, as opposed to information commoditization. In this section, we examine whether FDPs' product differentiation leads investors to differentially rely on some FDPs to a greater extent than others in assessing earnings performance, and if so, which aspects of FDPs' information production strategies are important in attracting investors to their products. Jollineau and Bowen [2023] note that many theories in accounting research can be conceptualized using conditional path analysis and recommend that researchers conceptually model hypothesized relations before specifying their empirical research design. Accordingly, we develop a conceptual path model linking product differentiation across FDPs to investor behavior.

Following Schaub [2018], we use the strength of the earnings response to a given FDP's earnings surprise to proxy for investors' reliance on that FDP's earnings information.[23] To the extent that investors rely on one FDP to a greater or lesser degree than another, we predict that the ERC will vary across FDPs. This is described as the association between earnings information and announcement-window abnormal returns being *moderated* across FDPs.[24] Figure 6, Panel A

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[22] In robustness tests presented in Table IA.3 in the internet appendix, we examine multiple entropy balanced sampling approaches and find similar results to those presented in Table 4, which increases the plausibility that the outcomes we document are driven by FDP differences rather than correlated differences in determinants.
[23] Schaub [2018] and Bochkay et al. [2022] both provide causal evidence of investors relying on FDPs in determining their trading response to earnings news.
[24] Jollineau and Bowen [2023] describe "moderation" as a conditional analysis that seeks to understand *when* X influences Y or *under what conditions* the relationship between X and Y varies in strength.

illustrates this moderation model with FDP interacting along the path between earnings information and investor response.

While the moderation model in Figure 6, Panel A allows us to examine *whether* investors rely on one FDP over another, it does not explain *why* investors might rely on one FDP over another. To explore why investors might rely on one FDP over another, we identify quality and salience as two product characteristics that FDPs can use to differentiate their earnings information when competing to satisfy investors' information demand. We expect that investors will rely more heavily on a given FDP's earnings information when it is of higher quality or is more salient among investors. Thus, in the conceptual path model, quality and salience represent "mediators" that help explain *why* investors' response to earnings information is moderated across FDPs.

We choose information quality as a mediating characteristic given that basic valuation theory predicts and empirical evidence finds that the market response to an earnings surprise should capture revisions in investors' expectations of future cash flows and/or firm risk (e.g., Garman and Ohlson [1980], Easton and Zmijewski [1989]). Therefore, in a frictionless market, investors' expectations should align more closely with an FDP's surprise when that FDP's earnings information is more accurate and/or better predicts future performance (i.e., is of higher quality).[25]

However, investors also face a variety of information processing costs in responding to earnings information. Therefore, investors may also respond more strongly to an FDP's surprise when that FDP's earnings information is less costly to process, *even if its earnings information is of lower quality*. We choose salience as a moderator because the salience of FDP information can be estimated from observable data and is relevant to investors' awareness and acquisition costs.[26]

[25] In our conversations with analysts, analysts often report differences in the quality of the earnings information they observe across FDPs. We provide additional analyses of difference in information quality across FDPs in Section 6.
[26] FDPs can also compete on their tangible subscription costs. Although we provide some information about subscription costs in footnote 11, they can vary widely and are generally proprietary and unobservable to researchers.

FDPs differentially invest in marketing and develop varied relationships with media outlets and brokerage houses, which may lead to differences in the salience and availability of their earnings information. In turn, investors' expectations should align more closely with an FDP's surprise when that FDP's earnings information is more salient among investors.

The final conceptual path model illustrated in Figure 6, Panel B represents a "mediated moderation" model where quality and salience mediate the moderation effect of FDPs in the earnings response relation (Kwan and Chan [2018]). Notably, on the right-hand side of the model, a direct moderation effect continues to extend from FDP to the earnings response relation. This path acknowledges that other unobserved product characteristics besides quality and salience (e.g., subscription costs, dissemination timeliness, etc.) may also explain the moderating role of FDPs. Empirically, to the extent that our proxies for FDPs' quality and salience account for all (some) of the statistically significant variation across FDPs in the earnings response relation, then we can infer that quality and salience "fully mediate" ("partially mediate") the moderating role of FDPs.

5.2. RESEARCH DESIGN

To test the hypothesized relations illustrated in our conceptual model, we develop a system of simultaneous equations based on three key elements that form the foundation of our research design. The first key aspect of this design is that the unit of observation is at the FDP-firm-quarter level. Each FDP k contributes one observation for each firm j for quarter t, such that there are exactly five observations for each firm-quarter in our sample. This allows us to translate the simple moderation model illustrated in Figure 6, Panel A into the following regression equation:

$$\begin{aligned} CAR_{jt} = {} & \beta_1\, FDP\ Surprise_{kjt} + \beta_2\, ZACKS_{kjt} + \beta_3\, CIQ_{kjt} + \beta_4\, BB_{kjt} + \\ & + \beta_5\, FSET_{kjt} + \beta_6\, FDP\ Surprise_{kjt} \times ZACKS_{kjt} + \beta_7\, FDP\ Surprise_{kjt} \times CIQ_{kjt} + \\ & \beta_8\, FDP\ Surprise_{kjt} \times BB_{kjt} + \beta_9\, FDP\ Surprise_{kjt} \times FSET_{kjt} + C \times Controls_{jt} + \\ & D \times (FDP\ Surprise_{kjt} \times Controls_{jt}) + \varepsilon_{kjt} \end{aligned} \tag{3}$$

In Equation (3), CAR_{jt} is the cumulative abnormal return for trading days [0,+1] around the earnings announcement date for firm j and quarter t.[27] The variable $FDP\ Surprise_{kjt}$ is the earnings surprise for firm j in quarter t provided by FDP k. $ZACKS_{kjt}$, CIQ_{kjt}, BB_{kjt}, and $FSET_{kjt}$ are indicator variables that represent the source of the surprise with I/B/E/S being the holdout FDP.

In Equation (3), β_1 captures the association between the I/B/E/S earnings surprise and the announcement window market reaction (i.e., the I/B/E/S ERC). The moderation effect in Figure 6, Panel A is tested using β_6 through β_9, the coefficients on the interaction terms between $FDP\ Surprise_{kjt}$ and the FDP indicator variables. Hence, Equation (3) allows us to test the difference between the I/B/E/S ERC and that of each of the other FDPs. We expect these coefficients to be positive (negative) to the extent that, on average, investors rely significantly more (less) on the earnings surprise produced by each FDP relative to that of I/B/E/S. Given that all five observations for each firm-quarter have identical values of CAR_{jt} and the sample of firm-quarters is the same across all five FDPs, only the presence of *within firm-quarter* variation across $FDP\ Surprise_{kjt}$ can give rise to coefficients β_6 through β_9 significantly differing from zero.

The second key aspect of our mediated moderation research design is that we develop proxies for the quality and salience mediation channels hypothesized in Figure 6, Panel B. Specifically, we identify seven relevant earnings surprise characteristics that can vary across FDPs for a given firm-quarter. We evaluate the quality of each FDP's earnings information based on measures of historical consensus forecast accuracy (*FDP Accuracy*) and the historical ability of the FDP's street earnings to predict future Compustat operating earnings (*FDP Predict Op Earnings)* and cash flows (*FDP Predict Op CF)*. In addition, we create a measure that captures the relative salience of each FDP's earnings information in the media (*FDP Media)*. Finally, we

[27] For earnings announcements after normal trading hours (i.e., after 4:00 PM ET), day 0 is the next trading day.

examine three characteristics that may reflect both the quality and salience of earnings information: the FDP's experience covering the firm (*FDP Experience*), the number of analysts contributing to the FDP's consensus forecast (*FDP Following*), and the extent to which the FDP's earnings information agrees with the earnings information of the other FDPs (*FDP Agreement)*.

Our focus is on the *relative* variation in the seven characteristics *within* a firm-quarter. Therefore, for each firm-quarter, we rank the five FDPs independently on *FDP Accuracy*, *FDP Predict Op Earnings*, *FDP Predict Op CF*, *FDP Media*, *FDP Experience*, and *FDP Following* from 0 (low) to 4 (high). We set tied values equal to the higher rank and scale the rankings to range from 0 to 1 (i.e., 0, 0.25, 0.5, 0.75, 1). Likewise, we scale *FDP Agreement* to range from 0 (i.e., no agreement with any of the other four FDPs) to 1 (agrees with the other four FDPs).[28]

We are interested in whether the quality and salience of the FDP's earnings information mediate the moderating effect of FDPs on the earnings response association. Therefore, the third and final key aspect of our research design is to expand Equation (3) into a system of equations following a recent approach developed by Kwan and Chan [2018] to estimate mediated moderation effects. This system includes an expanded specification of Equation (3) that adds interaction terms between *FDP Surprise* and the seven characteristics we use to proxy for quality and salience. To test the indirect effects of FDPs on the earnings response, *through* quality and salience, we also model the intermediate effects of FDPs on the seven mediator variables and their interactions with *FDP Surprise* in a series of intermediate equations for each mediator variable. We simultaneously estimate the resulting SEM system of equations using maximum likelihood estimation. We discuss the details of this methodology and the resulting system of equations in Appendix D.

[28] If an FDP-firm-quarter is missing data needed to calculate any FDP characteristic, we set the variable equal to zero. However, to distinguish ranks of zero when data is missing from those where the FDP has the lowest within firm-quarter rank, we also create indicator variables (i.e., "missing dummies") that equal one if data needed to calculate *FDP Accuracy*, *FDP Predict Op Earnings*, *FDP Predict Op CF*, or *FDP Media* is missing and zero otherwise.

As denoted in Equation (3), all of the SEM equations also include a series of control variables that vary at the firm-quarter level. These variables include the explanatory variables from Equation (1) as well as the main effects of the seven FDP characteristics, indicator variables equal to one if an FDP-firm-quarter observation is missing data needed to calculate any of the FDP characteristics, and *LnArticles*, the natural log of one plus the number of articles about firm *j* during the [0,+1] announcement window. Lastly, we control for the interactions of each of these variables with *FDP Surprise* following deHaan et al. [2023], who demonstrate that in interactive tests, control variables should generally be interacted with the relevant variables of interest for an unbiased estimation of the moderating effect of interest.

5.3. RESULTS

Panel A of Table 5 provides the mean and standard deviation for each FDP's relative rank of the seven FDP characteristics.[29] On average, I/B/E/S appears to exhibit the highest quality and most salient earnings information relative to the other FDPs, as evidenced by its higher mean rank for accuracy, cash flow predictive ability, experience, agreement with the other FDPs, dissemination in the media, and number of analysts included in the consensus forecast. Zacks, on the other hand, exhibits the lowest average rank for agreement with the other FDPs and number of analysts included in the consensus forecast, consistent with Zacks implementing a unique methodology relative to the other four FDPs. Capital IQ and Bloomberg are comparable with respect to the quality and salience of their earnings information but are consistently lower than I/B/E/S. FactSet exhibits the lowest average rank for experience but is comparable to Capital IQ and Bloomberg across the other six proxies of quality and salience. The standard deviations suggest that there is significant variation within each rank variable for the five FDPs, suggesting

[29] Consistent with 20.13 and 34.74 percent of firm-quarters missing the necessary data to calculate *FDP Predict Op Earnings* / *FDP Predict Op CF* and *FDP Media*, respectively, these variables often exhibit ranks equal to zero.

our measures of the relative quality and salience of FDP-produced earnings information vary significantly across FDPs from one firm-quarter to another.

Panel B of Table 5 provides univariate correlations among the FDP characteristics. The highest correlation is 0.650 between *FDP Predict Op Earn* and *FDP Predict Op CF*, while the second highest correlation is 0.151 between *FDP Accuracy* and *FDP Following* suggesting the seven FDP traits are generally distinct from one another.

We present the results of estimating Equation (3), excluding control variables, in column (1) of Table 6.[30] We find that the coefficient on $FDP\ Surprise_{kjt}$, which represents the average I/B/E/S ERC, is positive and significant (2.475, t = 42.80), consistent with prior literature. Also in column (1), the coefficients on the interaction between $FDP\ Surprise_{kjt}$ and BB and $FSET$ are significantly negative (-0.143, t = -4.09 and -0.318, t = -9.77, respectively).[31] In column (2), we estimate Equation (3) including the control variables and their interactions. Similar to column (1), we find that that the coefficient on $FDP\ Surprise_{kjt}$ is positive and significant (3.095, t = 26.91), while the coefficients on the interaction between $FDP\ Surprise_{kjt}$ and each of *BB* and *FSET* are significantly negative (-0.176, t = -4.87 and -0.313, t = -9.80).[32] Moreover, we find that the coefficient on the interaction between $FDP\ Surprise_{kjt}$ and *ZACKS* is also significantly negative (-0.067, t = -2.22). These results suggest that, on average, investors rely more heavily on the I/B/E/S earnings surprise than the surprise from Zacks, Bloomberg, or FactSet.[33] In column (3) we

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[30] Results in Table 6 are estimated using OLS with standard errors clustered by firm and announcement date. However, the coefficients are identical and all inferences unchanged if we instead use SEM with bootstrapped standard errors.

[31] In Table IA.4 in the internet appendix, we also estimate seemingly unrelated regressions without controls at the firm-quarter level where earnings surprise is measured according to each of the five FDPs separately, and we compare the ERC across the five different FDPs. We continue to observe a lower ERC for Bloomberg and for FactSet, relative to I/B/E/S and ERCs that are insignificantly different for Zacks and Capital IQ.

[32] Given that we standardize all non-indicator variables, the coefficients on the *FDP Surprise* and *FDP Surprise* × *FDP* terms represent the corresponding average effects when all the quality and salience ranks as well as the non-indicator control variables are at the sample mean and all indicator control variables are zero.

[33] We obtain similar results when the *CAR* measurement window is [-1,+1], [-1,+2], or [-1,+3] trading days around the earnings announcement, reducing concerns that timing differences in FDP dissemination are driving our results.

add the FDP characteristics and their interactions with $FDP\ Surprise_{kjt}$. Consistent with our expectations, we find that the ERC for a given FDP's earnings surprise is stronger when the FDP's earnings information is of higher quality and salience. With the exception of the coefficient on *FDP Surprise* × *FDP Experience,* which is statistically insignificant, the estimated coefficients on the six other interaction terms are all positive and significant at the five percent level or lower.[34]

Table 7 presents the results of our mediated moderation path analysis estimated using the SEM approach developed by Kwan and Chan [2018]. In particular, Table 7 shows how the moderating effect of each FDP documented in column (2) of Table 6 can be decomposed into the indirect effects through each of the seven mediators representing the quality and salience of the FDP's earnings information as well as the remaining direct effect of the FDP after accounting for these seven mediating variables. Thus, Table 7 depicts *why* Zacks, Bloomberg, and FactSet exhibit lower ERCs than I/B/E/S. For example, Zacks' lower ERC relative to I/B/E/S is attributable to its lower accuracy (*FDP Accuracy* = -0.035, p < 0.01) and fewer analysts contributing to the consensus forecast (*FDP Following* = -0.034, p < 0.05), while Bloomberg's and FactSet's lower ERCs relative to I/B/E/S are attributable to their reduced agreement with the other four FDPs (*FDP Agreement* = -0.061 and -0.070, p < 0.01 for Bloomberg and FactSet, respectively) and their lower accuracy (*FDP Accuracy* = -0.024 and -0.038, p < 0.01 for Bloomberg and FactSet, respectively). The indirect effects estimated in Table 7 can also be compared to the total effects from column (2) of Table 6 to provide a sense of how important each indirect effect is in explaining the total effects. For example, the indirect effect of *FDP Accuracy* accounts for approximately 52.2 percent (-0.035/-0.067) of the total difference in response coefficients between I/B/E/S and Zacks.

[34] If the FDP characteristics are time-invariant, readers solely interested in these characteristics without respect to FDP identity could view including the interactions of *FDP Surprise* × *FDP Identity* in column (3) as potentially over-controlling. In untabulated analyses, we exclude these interactions. The coefficient on *FDP Surprise* × *FDP Experience* becomes positive ($p < .01$), and all inferences are unchanged for the other six characteristics.

Moreover, our results suggest that the FDP-level traits we identify "fully mediate" the on-average differences between I/B/E/S and each of Zacks, Capital IQ, and Bloomberg, as evidenced by the insignificant coefficients on *FDP Surprise* × *ZACKS*, *FDP Surprise* × *CIQ*, and *FDP Surprise* × *BB* in column (3) of Table 6, and their corresponding insignificant direct effects in Table 7. Overall, the results in Tables 6 and 7 suggest that any on-average differences in the degree to which investors rely on one FDP's earnings information more than another's are at least in part driven by FDPs' product differentiation strategies. Our results are consistent with any mixture of investor behavior that involves investors either choosing to observe (i.e., purchase) some FDPs' earnings surprises and not others, or observing all FDPs' earnings surprises and weighing the higher quality or more salient surprises more heavily in their trading decisions.[35]

5.4. ROBUSTNESS

Our regression models in this set of analyses include many interaction terms, which can generate multicollinearity among the regressors. To investigate this concern, we conduct diagnostic tests (untabulated) examining VIFs from Equation (3). We find that for column (1) of Table 6, none of the VIFs exhibit signs of multicollinearity (i.e., all are well below 10). However, in columns (2) and (3) of Table 6, we observe VIFs greater than 10 on some interaction terms, which we attribute primarily to the inclusion of the missing data indicators and associated interaction terms. With the exception of *FDP Surprise* × *FDP Media* in column (3) of Table 6, the inflated VIFs are not observed on our coefficients of interest. Moreover, we examine an alternative model (untabulated) where we standardize all variables (including indicator variables) and require

[35] To investigate the possibility that investors average earnings information across FDPs, in untabulated analyses, we include the average earnings surprise across the five FDPs as an additional observation in our FDP-firm-quarter-level sample. We find that the average surprise has a significantly stronger ERC than any of the individual FDPs. However, when we compare this simple average with an average where each FDP's earnings surprise is weighted by its ranking across the seven measures of quality and salience, the weighted average ERC is significantly stronger, consistent with the market weighing an FDP's earnings surprise more heavily when it has greater quality and/or salience.

data for all seven measures of quality and salience for all observations. We continue to find similar results that the quality and salience of FDPs' earnings information incrementally explain investors' reliance on a given FDP. Moreover, this alternative model does not exhibit any concerning VIF statistics, suggesting that multicollinearity is unlikely to affect our inferences.

Finally, a potential alternative explanation for some of the results we observe in Table 6 is that ERC differences across FDPs are mechanical, whereby FDPs with on-average smaller earnings surprises, in absolute value, will exhibit higher ERCs. To help address this concern, we estimate alternative versions of Equation (3), where we instead examine a logistic regression model of whether the sign of the abnormal return reaction is more likely to be positive (negative) when a given FDP reports an earnings beat (miss) of at least $0.015. This alternative specification leads to inferences similar to those from Table 6. In particular, we find that investors rely on the earnings surprise that can be gleaned from I/B/E/S more than from Zacks, Bloomberg, and FactSet and that the association between the sign of abnormal return reaction and the sign of the FDP earnings surprise is stronger when the FDP's earnings information is of higher quality and salience. We present the results of these analyses in Table IA.5 in the internet appendix.

6. Additional Analyses

Given our finding that differences in the quality of earnings information produced across FDPs is relevant to investors, we perform additional analyses to gain a deeper understanding of whether these differences arise from discretionary FDP methodology choices. FDP-produced information is not required to follow GAAP and FDPs have wide discretion over their methodologies (e.g., Kaplan et al. [2021], Bochkay et al. [2022]).

We first explore whether the five FDPs systematically vary in the items they exclude from street earnings. We follow Bentley et al. [2018] and assume that the exclusion of transitory items represents higher-quality non-GAAP adjustments than the exclusion of persistent items. In Table IA.6 in the internet appendix we find that, relative to I/B/E/S, Zacks is less likely to exclude persistent items such as SBC and amortization expense from street earnings, but more likely to exclude income decreasing transitory items, consistent with Zacks' "adjust and include" accounting methodology. We further find that Bloomberg (FactSet) tends to exclude more (fewer) items from street earnings relative to I/B/E/S. In particular, Bloomberg is more likely to exclude SBC, amortization expense, and income decreasing transitory items from street earnings, while FactSet is less likely to exclude amortization expense and income decreasing transitory items.

Given that FDPs' accounting methodologies appear to shape their street earnings exclusions, we then investigate whether these methodology differences are associated with variation in the predictive ability of street earnings. Based on our exclusion analyses and our discussion of FDP methodologies in Section 3, we expect larger differences for firm-quarters with high levels of SBC or with unexpected items. As presented in Table IA.7 in the internet appendix, we find that, relative to I/B/E/S, Zacks street earnings are more (less) strongly associated with future operating earnings (cash flows) for firm-quarters with high SBC, consistent with Zacks uniformly including SBC expense in street earnings and SBC having a higher (lower) association with future operating earnings (cash flows). We further find that Zacks and Bloomberg street earnings improve in predictive ability relative to I/B/E/S for firm-quarters with unexpected items, consistent with these FDPs taking an active role in adjusting or excluding these items, which are often less predictive of future firm outcomes (Bratten et al. [2024]). Taken together, these results provide evidence that the quality of FDP earnings information varies with features of the FDPs' accounting methodologies.

7. *Conclusion*

Earnings information compiled by forecast data providers plays an important role in capital markets and academic research. We provide novel evidence about the prevalence, magnitude, and implications of differences in the earnings information provided by the five major FDPs – Bloomberg, Capital IQ, FactSet, I/B/E/S, and Zacks. These FDP differences have implications for the efficiency of the price response to earnings, consistent with FDP differences increasing investors' costs of processing earnings information and reducing market efficiency. We also observe that the market response associated with a given FDP's earnings surprise varies in accordance with its expected quality and salience. On average, relative to the other FDPs, I/B/E/S ranks highly in our measures of quality and salience and our estimates suggest that investors rely more heavily upon its earnings information than that of some of the other prominent FDPs we examine, validating its use as a representative FDP in academic research.

Although these inferences are robust to various alternative specifications, variable definitions, and sensitivity tests reported throughout our study, a limitation of our study is that many of our results are inherently associational in nature. For example, while prior literature provides causal evidence of investors relying on FDP-produced earnings information (Schaub [2018], Bochkay et al. [2022]), observing a stronger market reaction associated with a given FDP's earnings surprise may suggest that the FDP's information better reflects the marginal investor's inherent earnings expectations as opposed to the marginal investor relying more heavily on the FDP in forming their expectations. While future research may help validate whether our results are causal in nature, our study clearly demonstrates that, in modern capital markets, "consensus" earnings information is not a standardized commodity, but rather a differentiated product with properties that vary across FDPs in accordance with their competitive product-market strategies.

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APPENDIX A
Summary of FDP processes for collecting forecasts and forming street earnings

I/B/E/S

I/B/E/S gathers earnings forecasts and other data from hundreds of brokerage and independent analysts who track companies as part of their investment research work. I/B/E/S calculates a mean consisting of estimates utilizing the same accounting standards (basis).

Most institutional clients prefer to view estimates on an "operating" basis, reflecting the majority of the analysts covering a security. Consequently, I/B/E/S follows a 'majority' policy, where the accounting basis of each company estimate is determined by the basis used by the majority of contributing analysts.

Once the majority basis has been established, contributing analysts in the minority may keep their original estimates, or are also given the opportunity to adjust to the majority basis. On rare occasions, the majority basis may be revised as additional analysts are heard from or as some change their opinion. In all cases, appropriate footnotes are added to the I/B/E/S database stating the appropriate basis of each estimate, and if the item has been included or excluded from the mean estimate. If an estimate has not been updated for 180 days, the estimate is filtered, footnoted, and excluded from the mean.

The goal of I/B/E/S is to present actual on the same basis as the consensus mean estimates. In many cases, the company's reported figure contains unusual or one-time items that the majority of the analysts may include/exclude from their published forecasts. I/B/E/S adjusts the company's reported actual to reflect the basis that the majority of the contributors used in their estimates. I/B/E/S takes on this additional step to ensure consistency in methodology and that the miss/beat type of surprise calculations are done on the same basis.

Source: I/B/E/S documents

Capital IQ

Estimate researchers are rigorously trained to collect information directly from reports and to review electronically entered data. Researchers review the data for consistency with definitions and compare values with the current consensus value. Researchers also note differences between the data item captured and data item definitions. They may perform minor calculations to arrive at a figure that fits the definition or to arrive at a figure that is consistent with the consensus value.

All of the available analysts' estimates may not necessarily be included in the Consensus. Detail estimates excluded from the consensus numbers are flagged. Textual footnotes that describe the reason behind the exclusion are available. Some common reasons for exclusion include estimates based on different methodologies, stale estimates and estimates that have not been revised or confirmed following a significant event, and outliers. Estimates are considered stale after 180 calendar days.

For many companies, the Actuals are not comparable to the S&P Capital IQ Fundamentals. Actuals are collected to supplement the Estimates and to provide a comparable value based on the Consensus methodology. Therefore, Actuals may not reconcile back to the reported GAAP financial statements. Examples of differences could include treatment of one-off items, stock-based compensation, or amortization of goodwill.

Source: Capital IQ documents

FactSet

Broker estimates can be received and processed in a multitude of formats of the broker's choosing. The main two types of formats are manual contribution and automatic contribution. Manual contribution involves FactSet pulling figures from PDF reports while automatic contribution involves the broker sending Excel files to FactSet. The contributor can choose the format and frequency in which they would like to contribute to FactSet Estimates.

FactSet Estimates does not make or alter estimates received from contributors, but does however, convert currency and convert units when appropriate.

The consensus "window" refers to the time period associated with estimates used in the consensus. By default, consensus estimates calculated by FactSet are based on estimates that have been validated via broker research within the past 100 days. For the fourth quarter, FactSet dynamically extends the default 100-day window to the last actual Q3 report date, but no more than 150 days. Using a Variable Window in these cases ensures that broker contributions from the end of the third quarter do not get excluded due to a lag of report time.

FactSet's EPS estimates reflect the majority methodology, i.e., what the Market is expecting as a reference for the company's numbers.

Source: FactSet documents

Zacks

Zacks uses an "adjust and include" methodology that adjusts both forecasted and reported earnings to a standardized Zacks measurement basis, referred to as before non-recurring items ("BNRI"), that excludes non-recurring items while including stock-based compensation expense. The consensus estimate is the average of all the current estimates made available by brokerage analysts. It is Zacks policy to make sure that the Zacks Consensus reflects only those forecasts that are relatively fresh. For each type of forecast, Zacks maintains a refreshment window of time. If any individual forecast cannot be re-affirmed within this time period, it will be removed from the Consensus until it can be re-affirmed or updated.

When a company issues guidance, Zacks will drop all individual estimates made prior to the guidance that fall outside the range of that guidance. Zacks then includes all estimates made after the date of the guidance. This policy removes outliers that are based on old information and may cause the Zacks consensus of EPS BNRI to jump on the day that guidance is issued to fall within the guidance range Zacks maintains a pre-announcement surprise database that allows investors to gauge the effect that changes in guidance may have on the stock price.

Source: Zacks documents

<u>Bloomberg</u>

Bloomberg excludes stale estimates and ones that are measured on a different basis. An estimate is stale if it was provided more than 30 days prior to the most recent report date, guidance, or a corporate action. Bloomberg also performs statistical checks that look for outliers based on deviation from the consensus. On top of these checks, Bloomberg analysts review each consensus to ensure the highest level of consensus integrity and data quality.

BEst (Bloomberg Estimates) EPS reflects the consensus estimate for adjusted earnings per share. The consensus estimate is the mean of sell-side analyst estimates.

Source: Bloomberg

APPENDIX B
Description of processes used to download forecasts and street earnings from various FDPs

I/B/E/S

We downloaded I/B/E/S data from WRDS. For consistency with the other data providers, we begin with the I/B/E/S unadjusted surprise summary file (surpsumu), which contains quarterly EPS announcement dates and street earnings along with the associated I/B/E/S consensus mean forecast and standard deviation as of the time of the earnings announcement. However, the surprise summary file does not contain the number of analysts contributing to the final consensus forecast. Therefore, we link the surprise file with the I/B/E/S summary file (statsum_epsus) to obtain analyst following from the most recent statistical period (statpers) prior to the earnings announcement. We merge the I/B/E/S data to the CCM dataset using the WRDS iclink macro and fiscal period end date.

Capital IQ

We obtained an Xpressfeed subscription to the S&P Capital IQ Estimates database delivered in the form of a Postgresql database. We used SQL queries to merge the latest available consensus estimates with their street earnings for each firm-quarter within the Capital IQ database. We use Capital IQ's internal split adjustment factors and majority basis identifier (estimatevarid) to obtain unadjusted values on the majority basis as of the EPS announcement date. We then used the WRDS linking table provided by S&P to link Capital IQ firm IDs to Compustat GVKEYs. Finally, we merge the Capital IQ data to the CCM dataset using GVKEY and fiscal period end date.

FactSet

We obtained a direct data feed subscription to the FactSet Consensus Estimates database delivered in the form of a Snowflake database. We used SQL queries to merge the latest available consensus estimates with their street earnings for each firm-quarter within the FactSet database. We obtain CUSIP identifiers for each FactSet ID (FSYM_ID) from the FactSet SYM_CUSIP file, and then merge FactSet to the CCM dataset using CUSIP and fiscal period end date. The FactSet EPS data are split-adjusted. We manually examined the data and hand checked several original earnings announcement press releases and news articles to determine that the FactSet data generally follows the same split adjustment procedure as the other databases. Therefore, we use the corresponding I/B/E/S split adjustment factors to unadjust the FactSet data to announcement date values.

Zacks

We downloaded Zacks data from WRDS. We obtained quarterly EPS announcement dates and street earnings along with the associated Zacks consensus mean forecast, standard deviation, and analyst following as of the time of the announcement from the Zacks EPS surprise file (eps_surp). We merged the EPS surprise file with the Zacks firm info file (company_info) to obtain CUSIP identifiers for each Zacks ID (zid), and then merge Zacks to the CCM dataset using CUSIP and fiscal period end date. The Zacks EPS surprise file on WRDS only offers split-adjusted data. We manually examined the Zacks data and hand checked several original announcement press releases and news articles to determine that the Zacks data generally follow the same split adjustment procedure as the other databases. Therefore, we use the corresponding I/B/E/S split adjustment factors to unadjust the Zacks data to announcement date values.

Bloomberg

We begin with a sample of firm-quarters from 2002 to 2017 with non-missing assets, sales, and common equity, and with assets and sales above $100 million, and share price above $1, from the Compustat-CRSP merged file. Because Bloomberg does not allow for forecasts and street earnings to be downloaded *en masse*, we proceed as follows. We download the Bloomberg firm names and tickers for firms in the Russell 3000 in each of the years 1999 through 2020. We match these Bloomberg firm names and tickers to the firm names and tickers in Compustat-CRSP using both textual analysis and some hand-matching. For the other Compustat-CRSP firms which were not matched to the Russell 3000 firms, we hand-collected their Bloomberg tickers. For each of the Bloomberg tickers we matched to Compustat-CRSP, we download both GAAP and market forecasts (IS_COMP_EPS_GAAP(AE=E) and IS_COMP_EPS_MARKET(AE=E), respectively) and GAAP and street earnings (IS_COMP_EPS_GAAP(AE=A) and IS_COMP_EPS_MARKET(AE=A), respectively) from Bloomberg into spreadsheets for periods beginning as early as 1989 (depending on data availability) using Bloomberg's BQL function, similar to an application programming interface or API. The Bloomberg EPS data are split-adjusted. We manually examined the data and hand checked several original announcement press releases and news articles to determine that the Bloomberg data generally follows the same split adjustment procedure as the other databases. Therefore, we use the corresponding I/B/E/S split adjustment factors to unadjust the Bloomberg data to announcement date values.

Part of the difficulty with using Bloomberg data for large-sample academic purposes is its reliance on tickers which, in some cases, change or are supplanted over time. For example, a firm which was once associated with ticker ABC until it was delisted is now referred to with a numerical ticker in Bloomberg. In some cases, new Bloomberg tickers can be located but in other cases, we could not locate the new ticker. Thus, we believe that the Bloomberg data we downloaded likely understates the number of companies actually covered by Bloomberg.

APPENDIX C
Variable Definitions

Variable		Definition
Abnormal Depth	=	Daily depth is the average of the time-weighted best bid dollar depth and best offer dollar depth (Millisecond Intraday Indicators by WRDS data item 'BestBidDepth_Dollar_tw' and 'BestOfrDepth_Dollar_tw'). Abnormal depth is the log of (the average daily depth over trading days [0,1] divided by the average daily depth over trading days [-41,-11]).
Abnormal Price Impact	=	Daily price impact is the average percent price impact of each trade over a 5-minute window (Millisecond Intraday Indicators by WRDS data item 'PercentPrice Impact_LR_Ave'). Abnormal impact is the weighted average daily impact over trading days [0,1] divided by the weighted average daily impact over trading days [-41,-11]). Daily impacts are weighted based on total number of trades during market hours (Millisecond Intraday Indicators by WRDS data item 'variable total_n_trades_m'). Abnormal impact is not logged because the ratio is frequently negative.
Abnormal Spread	=	Daily spread is average percent effective spread (Millisecond Intraday Indicators by WRDS data item 'EffectiveSpread_Percent_Ave'). Abnormal spread is the log of (the weighted average daily spread over trading days [0,1] divided by the weighted average daily spread over trading days [-41,-11]). Daily spreads are weighted based on total number of trades during market hours (Millisecond Intraday Indicators by WRDS data item 'total_n_trades_m').
Abnormal Volatility	=	Daily volatility is the sum of squared logarithmic returns for each 5-minute interval for each trading day during regular trading hours from 9:30 to 4:00 EST. Abnormal volatility is the log of (the average daily volatility over trading days [0,1] divided by the average daily volatility over trading days [-41,-11]). We use the TAQ Millisecond WCT files.
abs(ΔIB)	=	Absolute value of percentage change in income before extraordinary items (Compustat data item 'IBQ') from the prior year, same quarter.
abs(ΔShares)	=	Absolute value of percentage change in common shares for diluted EPS (Compustat data item 'CSHFDQ') from the prior quarter.
abs(Special Items)	=	Absolute value of special items (Compustat data item 'SPIQ') scaled by absolute value of income before extraordinary items (Compustat data item 'IBQ').
abs(Surprise)	=	The absolute value of the I/B/E/S street EPS value less the I/B/E/S mean consensus forecast, scaled by price as of day *t-2* relative to the earnings announcement date.
Activation Delay	=	Natural logarithm of one plus the time (in minutes) from the earnings press release time until I/B/E/S actual value is activated (I/B/E/S data item 'ACTDATS' less 'ANNDATS').
BB	=	Indicator variable that equals one if the data are from Bloomberg, zero otherwise.

BTM	=	Book to market ratio of common equity. Equal to book value of common equity (Compustat data item 'CEQQ') scaled by market value of common equity (Compustat data item 'CSHOQ' times 'PRCCQ').
CAR	=	Cumulative abnormal return from trading days [0,+1] around the earnings announcement date, defined as the cumulative return on the stock of firm *j* less the cumulative return on the CRSP value-weighted market index, and multiplied by 100. If the earnings announcement occurs after normal trading hours (i.e., after 4:00 PM EST), then day 0 is the next trading day.
CIQ	=	Indicator variable that equals one if the data are from Capital IQ, zero otherwise
Dispersion		Standard deviation of I/B/E/S consensus EPS forecast values (I/B/E/S data item 'SURPSTDEV' from the surprise file), scaled by price as of day *t-2* relative to the earnings announcement date.
FDP Accuracy	=	The average within firm-quarter rank of the FDP's consensus forecast accuracy over the prior 1 to 20 quarters where we require coverage by all five FDPs, ranked between 0 (lowest) and 4 (highest) for each firm-quarter with tied values assigned to the higher rank, scaled by 4; accuracy is defined as the absolute value of the FDP's street EPS value less the FDP's consensus EPS forecast, scaled by price as of day *t-2* relative to the earnings announcement date, and multiplied by −1.
FDP Agreement	=	The number of other FDPs for which the FDP's street earnings per share agrees within $0.015 for a given firm-quarter, scaled by 4.
FDP Experience	=	The number of quarters the FDP has been following the firm, ranked between 0 (lowest) and 4 (highest) for each firm-quarter with tied values assigned to the higher rank, scaled by 4.
FDP Following	=	The number of individual analysts in the FDP's consensus, ranked between 0 (lowest) and 4 (highest) for each firm-quarter with tied values assigned to the higher rank, scaled by 4.
FDP Media	=	The number of RavenPack articles over the [0,+1] day window around the quarterly earnings announcement about the firm that contain the amount of both the FDP's forecasted and street EPS in the article headline, ranked between 0 (lowest) and 4 (highest) for each firm-quarter with tied values assigned to the higher rank, scaled by 4.
FDP Predict Op CF	=	The coefficient estimates from within FDP-firm time series rolling regressions of *Future Op CF* regressed on *FDP Street* separately for I/B/E/S, Zacks, Capital IQ, Bloomberg, or FactSet, ranked between 0 (lowest) and 4 (highest) for each firm-quarter with tied values assigned to the higher rank, scaled by 4; for these time-series regressions we require a minimum of 4 and a maximum of 20 lagged quarterly observations and require coverage by all five FDPs for each lagged observation. *Future Op CF* is defined as the sum of quarterly operating cash flows (derived from Compustat data item 'OANCFY') over quarters *t+1* to *t+4*, and scaled by total assets for quarter *t* (Compustat data item 'ATQ'), and multiplied by 100.

FDP Predict Op Earn	=	The coefficient estimates from within FDP-firm time series rolling regressions of *Future Op Earnings* regressed on *FDP Street* separately for I/B/E/S, Zacks, Capital IQ, Bloomberg, or FactSet, ranked between 0 (lowest) and 4 (highest) for each firm-quarter with tied values assigned to the higher rank, scaled by 4; for these time-series regressions we require a minimum of 4 and a maximum of 20 lagged quarterly observations and require coverage by all five FDPs for each lagged observation. *Future Op Earnings* is defined as the sum of operating EPS (Compustat data item 'OEPSXQ') multiplied by common shares for diluted EPS for the quarter (Compustat data item 'CSHFDQ') over quarters *t+1* to *t+4*, and scaled by total assets for quarter *t* (Compustat data item 'ATQ'), and multiplied by 100.
FDP Surprise	=	For each FDP, the street EPS value less the FDP's mean consensus forecast, scaled by price as of day *t-2* relative to the earnings announcement date
FSET	=	Indicator variable that equals one if the data are from FactSet, zero otherwise.
Guidance	=	Indicator variable that equals one if the firm issued earnings guidance for quarter *t*, zero otherwise.
IBES	=	Indicator variable that equals one if the data are from I/B/E/S, zero otherwise
Inst Own	=	The percentage of shares held by 13F institutions as of the end of the most recent calendar quarter before the earnings announcement date.
Max Less Min Surp	=	The maximum less the minimum earnings surprise across the five FDPs, scaled by price as of day *t-2* relative to the earnings announcement date, and multiplied by 100.
Miss and Beat	=	Indicator variable that equals one if at least one FDP earnings surprise indicates the firm missed the consensus forecast (i.e., surprise is less than or equal to -0.015) and at least on FDP earnings surprise indicates the firm beat the consensus forecast (i.e., surprise is greater than or equal to 0.015).
MRT	=	Equal to $\frac{\mathrm{RET}_{[0,1]}}{\mathrm{RET}_{[0,31]}}+\frac{\mathrm{RET}_{[0,2]}}{\mathrm{RET}_{[0,31]}}+\ldots\frac{RET_{[0,30]}}{RET_{[0,31]}}+\ 0.5$, where $\mathrm{RET}_{[0,t]}$ is the buy-and-hold return up to and including hour *t* following the earnings announcement. To reduce the influence of small denominators and extreme return overreactions, each return fraction is winsorized at -1 and 1. We use the TAQ Millisecond WCT files.
MVE	=	Natural log of common shares outstanding (Compustat data item 'CSHOQ') times share price at the end of the fiscal quarter (Compustat data item 'PRCCQ').
LnArticles	=	The natural logarithm of the number of news articles about the company over the [0,+1] day window around the quarterly earnings announcement.
Q4	=	Indicator variable that equals one if the quarter is the fourth fiscal quarter, and zero otherwise.
Ret Vol	=	Standard deviation of daily stock returns over the fiscal quarter (Crsp data item 'RET').
SBC High		Indicator variable that equals one if stock compensation expense per share (Compustat data item 'STKCOQ' scaled by 'CHSOQ') is above the sample median by calendar quarter; zero otherwise.

Std Dev Surp	=	The standard deviation of earnings surprise across the five FDPs, scaled by price as of day *t-2* relative to the earnings announcement date, and multiplied by 100.
Stock Split	=	Indicator variable that equals one if there was a stock split between the earnings announcement date and the date the data are collected, and zero otherwise.
abs(Surprise)	=	The absolute value of the I/B/E/S street EPS value less the I/B/E/S mean consensus forecast, scaled by price as of day *t-2* relative to the earnings announcement date.
Unique Following	=	Number of unique analyst followings across the five FDPs.
Unexpected Item	=	Indicator variable that equals one if a company reports any of the following eight charges/gains in a quarter: a large restructuring charge, a large acquisition expense or gain, net credit or charge to reserves for bad debts from loan recoveries or charge-offs, nonrecurring income taxes, settlement of litigation or insurance, asset write-down, goodwill impairment, and large special items (Compustat data items 'RCPQ', 'AQPQ', 'NCOQ', 'NRTXTQ', 'SETPQ', 'WDPQ', 'GDWLIPQ', and 'SPIQ'); zero otherwise. An item is classified as large if it is in the top decile of the sample distribution of its absolute value.
ZACKS	=	Indicator variable that equals one if the data are from Zacks, zero otherwise.

APPENDIX D
Description of the estimation of mediated moderation using the Variable System approach

As shown in Panel A of Figure 6, we examine how the relation between FDP earnings surprise (*FDP Surprise*) and the two-day cumulative abnormal return starting on the earnings announcement date (*CAR*) varies with the identity of the FDP (*BB*, *CIQ*, *FSET*, or *Zacks*), relative to I/B/E/S as our holdout FDP. As shown in Figure D1, this is commonly denoted in the conditional path analysis literature as a moderation model where a moderator *W* (i.e., *FDP*) moderates the causal path from *X* (i.e., *FDP Surprise*) to *Y* (i.e., *CAR*) (Kwan and Chan [2018], Jollineau and Bowen [2023]).

In the vocabulary of conditional path analysis, we then examine whether the moderating effect of *W* (FDP) is mediated by FDP characteristics, denoted *M* in the abstract path model, to better understand *why* FDP identify moderates the earnings response relation. The conditional path analysis literature (e.g., Kwan and Chan [2018]; Hayes [2022]) refers to this type of canonical relationship as Type II mediated moderation, as depicted in Figure D2 (see Kwan and Chan [2018], Figure 5a). Thus, as shown in Panel B of Figure 6, in our model *M* represents either the quality or salience of the FDP's earnings information. Empirically, we examine seven proxies of quality and salience, including historical accuracy (*FDP Accuracy*), predictive ability (*FDP Predict Op Earn* or *FDP Predict Op CF*), experience (*FDP Experience*), the extent to which the FDP's earnings information agrees with the earnings information of the other FDPs (*FDP Agreement*), dissemination by the media (*FDP Media*), and the number of analysts contributing to the FDP's consensus forecast (*FDP Following*).

Kwan and Chan [2018] propose an integrated approach – the Variable System (VS) approach – for the analysis of Type II mediated moderation using structural equation modeling (SEM). Moreover, they develop an R software package that implements the VS approach.[36] The working model (i.e., the mathematical transformation that is derived from the conceptual model and estimated using SEM) for Type II mediated moderation using the VS approach is shown in Figure D3. To estimate the indirect mediated moderation effect of *W* through *M* on the relation between *X* and *Y*, VS estimates three model equations simultaneously. The first model equation regresses *MX* on *WX*, *X*, and *W*, with the coefficient of interest being that on *WX* (represented by α_1 in Figure D3). The second model equation regresses *M* on *WX*, *X*, and *W*, with the coefficient of interest being that on *WX* (represented by α_3 in Figure D3). Finally, the third model equation regresses *Y* on *WX*, *X*, *W*, *MX*, and *M*, with the coefficients of interest being those on *MX* and *M* (represented by α_2 and α_4, respectively, in Figure D3). The indirect mediated moderation effect of *W* through *M* on the relationship between *X* and *Y* is calculated as $\alpha_1 \times \alpha_2 + \alpha_3 \times \alpha_4$.

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[36] The VS R package is available from GitHub at https://github.com/VSquanpsy/VS with an accompanying website at https://vsquanpsy.wixsite.com/home (accessed February 14, 2025). Using the VS package, users specify the conceptual model and the package assists in building and estimating the system of equations underlying the conceptual model. Specifically, this program 1) transforms the conceptual model into the SEM working model; 2) generates a VS dataset that includes all the key variables and their interaction terms as needed; 3) creates additional parameters and model constraints for testing the conditional direct and indirect effects of theoretical interest; 4) runs the SEM analysis of the specified model; and 5) prepares an output file with all major results summarized in a readable format (Kwan and Chan [2018]).

Using this approach, we simultaneously estimate the four direct effects for each of the non-I/B/E/S FDPs (*BB*, *CIQ*, *FSET*, or *ZACKS*) and the 28 indirect effects for each of the four non-I/B/E/S FDPs and each of the seven FDP characteristics (*FDP Accuracy*, *FDP Predict Op Earn*, *FDP Predict Op*, *FDP Experience*, *FDP Agreement*, *FDP Media*, and *FDP Following*). This process results in 15 equations being estimated simultaneously – seven model equations where the dependent is each of the seven FDP characteristics and the four independent variables of interest are *FDP Surprise* × *ZACKS*, *FDP Surprise* × *CIQ*, *FDP Surprise* × *BB*, and *FDP Surprise* × *FSET*; seven model equations where the dependent variable is each of the seven FDP characteristics interacted with *FDP Surprise* and the four independent variables of interest are *FDP Surprise* × *ZACKS*, *FDP Surprise* × *CIQ*, *FDP Surprise* × *BB*, and *FDP Surprise* × *FSET*; and one model equation where the dependent variable is *CAR* and the fourteen independent variables of interest are each of the seven FDP characteristics and each of the seven FDP characteristics interacted with *FDP Surprise*.

For example, the indirect effect of *ZACKS* through historical forecast accuracy (*FDP Accuracy*) on the earnings response (*CAR*), which is estimated as -0.035 in Table 7, is estimated using the working model shown below in Figure D4. It is equal to the product of the coefficient estimate on *FDP Surprise* × *ZACKS* when *FDP Surprise* × *FDP Accuracy* is the dependent variable (-0.375, untabulated) and the coefficient estimate on *FDP Surprise* × *FDP Accuracy* when *CAR* is the dependent variable (0.094, as presented in Table 6, column (3)) plus the product of the coefficient estimate on *FDP Surprise* × *ZACKS* when *FDP Accuracy* is the dependent variable (-0.012, untabulated) and the coefficient estimate on *FDP Accuracy* when *CAR* is the dependent variable (0.005, untabulated). In other words, as depicted in Figure D4, this indirect effect is equal to $\alpha_1 \times \alpha_2 + \alpha_3 \times \alpha_4$ (-0.035 = -0.375 × 0.094 + -0.012 × 0.005). Each of the other 27 indirect effects presented in Table 7 are estimated using the same process presented in Figure D4, where the FDP identity is used in place of *ZACKS* and each of the FDP characteristics is used in place of *FDP Accuracy*.

Lastly, the direct effect of each FDP's identity on the earnings response coefficient (depicted by α_5 in Figures D3 and D4) is simply the residual effect between *FDP Surprise* × *FDP Indicator* and *CAR* after accounting for the seven FDP characteristic mediators (Jollineau and Bowen [2023]). We calculate the statistical significance of the direct and indirect effects from the SEM model using bootstrapped standard errors, as is standard in the conditional path analysis literature (Preacher and Hayes [2008]; Jollineau and Bowen [2023]).

Figure D1: Simple moderation conceptual model

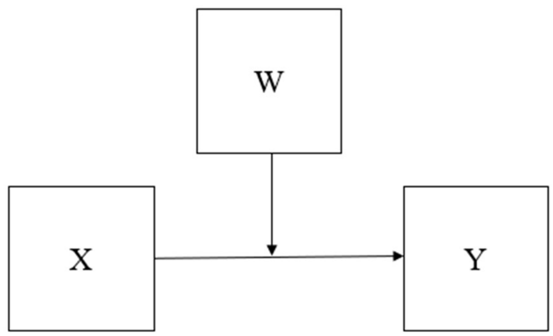


Figure D2: Type II mediated moderation conceptual model

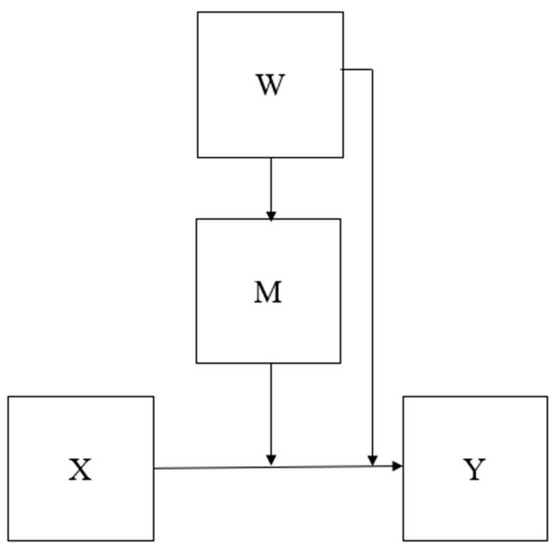


Figure D3: Type II mediated moderation working model

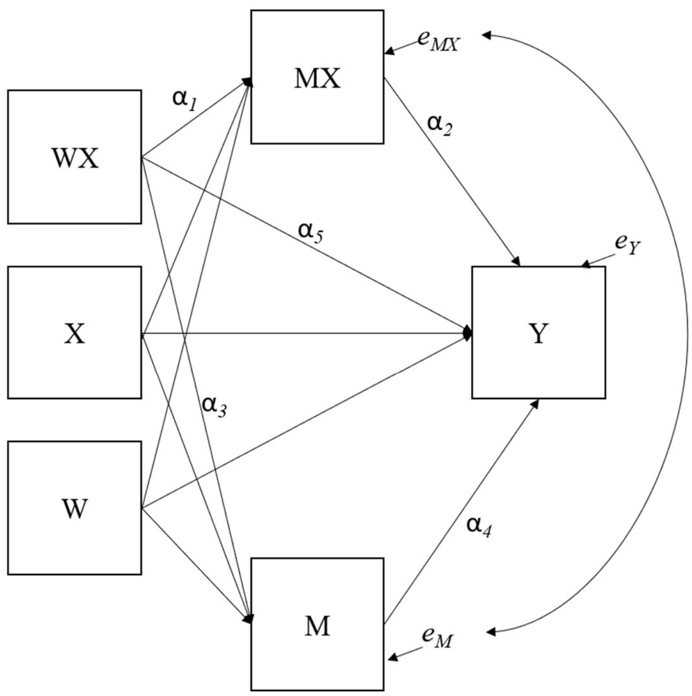


Figure D4: Example working model for the indirect effect of *ZACKS* through historical accuracy (*FDP Accuracy*)

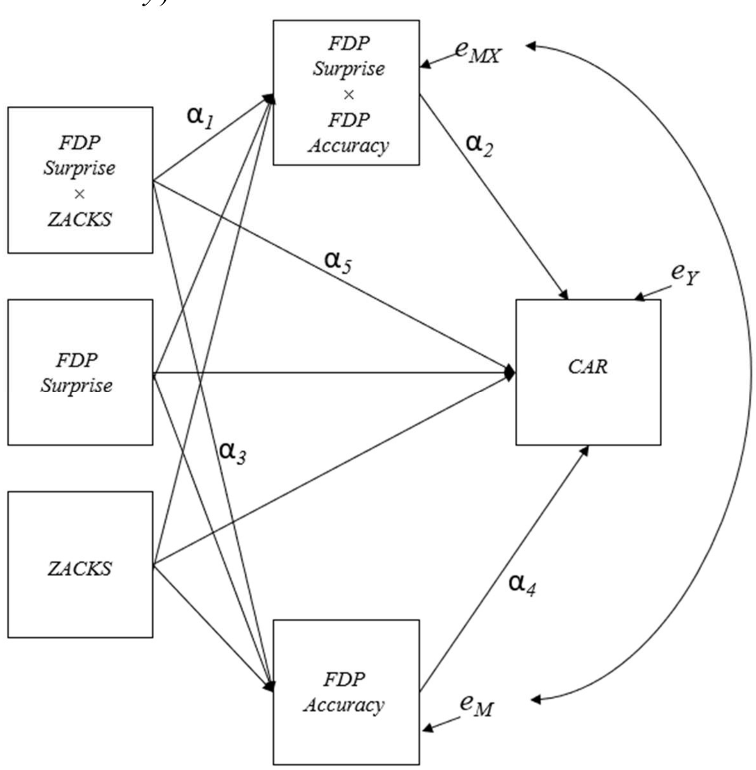
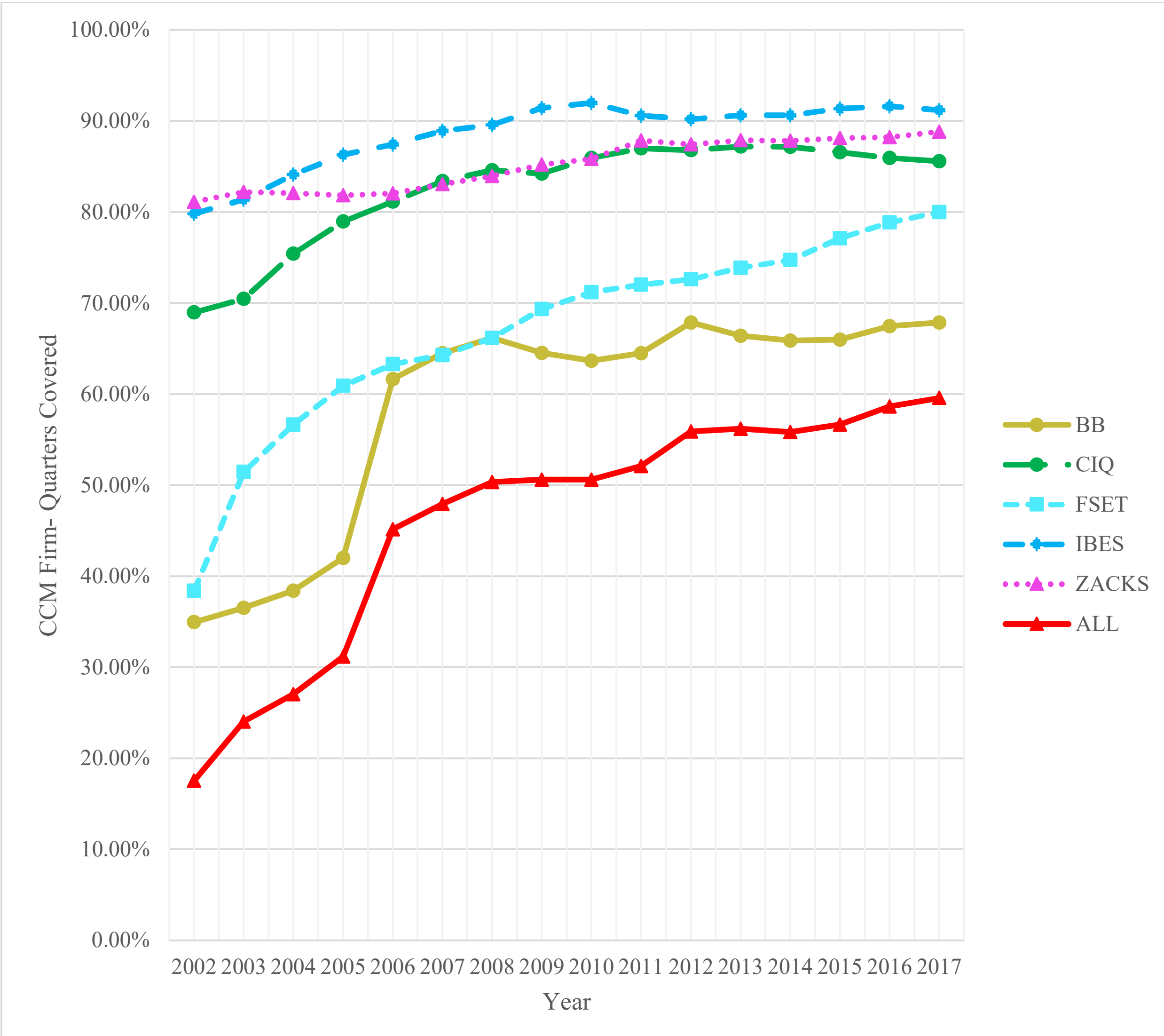
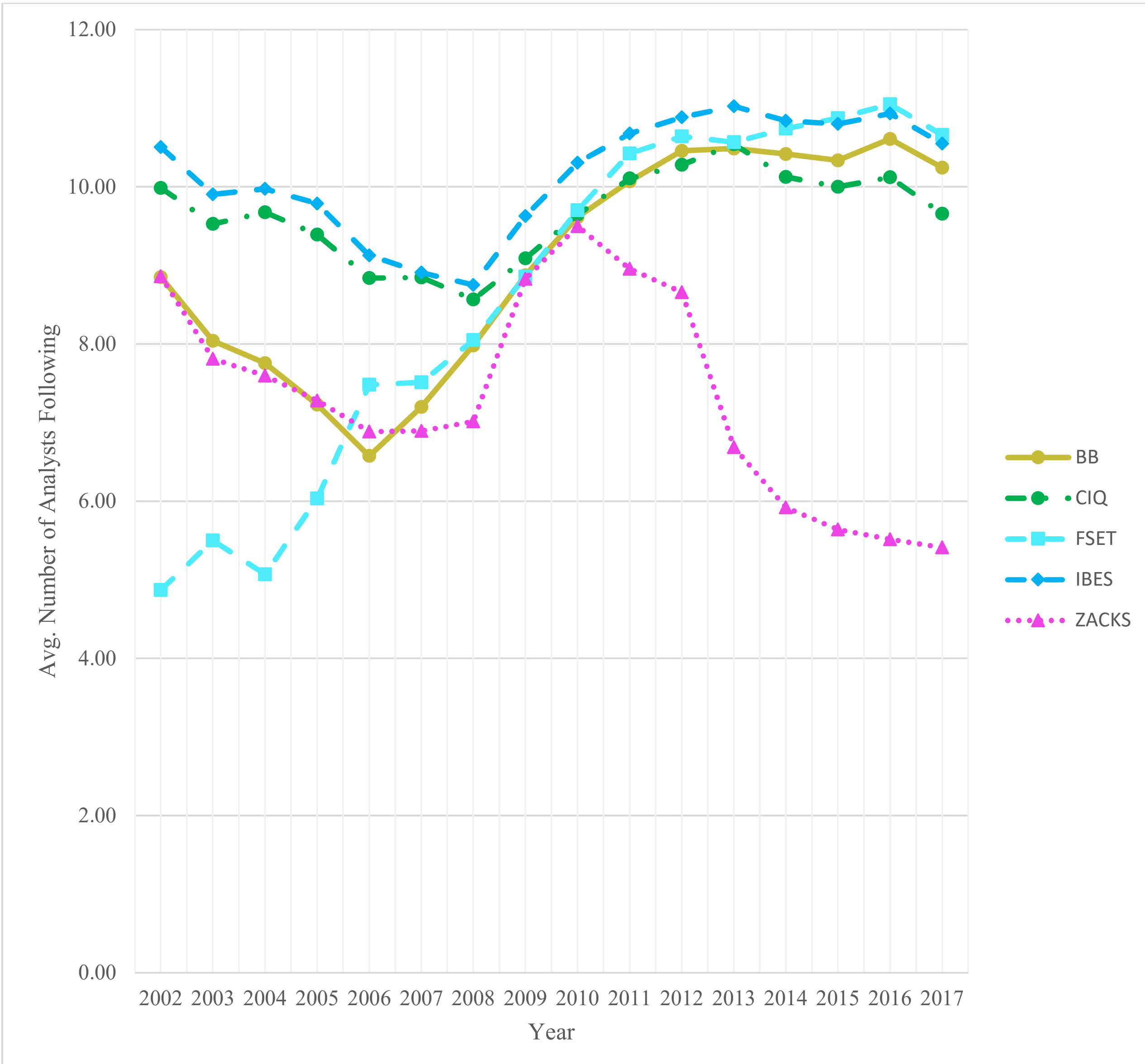


FIGURE 1
Firm-Quarter Coverage by FDP



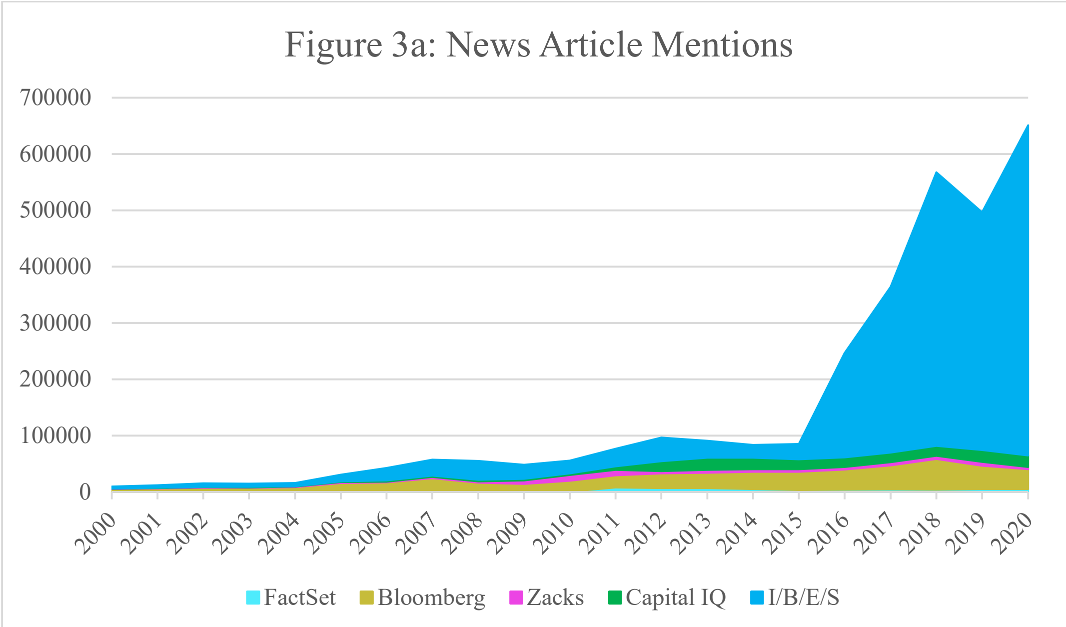
This figure provides details of the coverage of the 209,035 firm-quarters contained in the Compustat-CRSP merged file by each of the five forecast data providers, Bloomberg (BB), Capital IQ (CIQ), FactSet (FSET), I/B/E/S (IBES), and Zacks (ZACKS). ALL refers to the firm-quarters covered by all five FDPs.

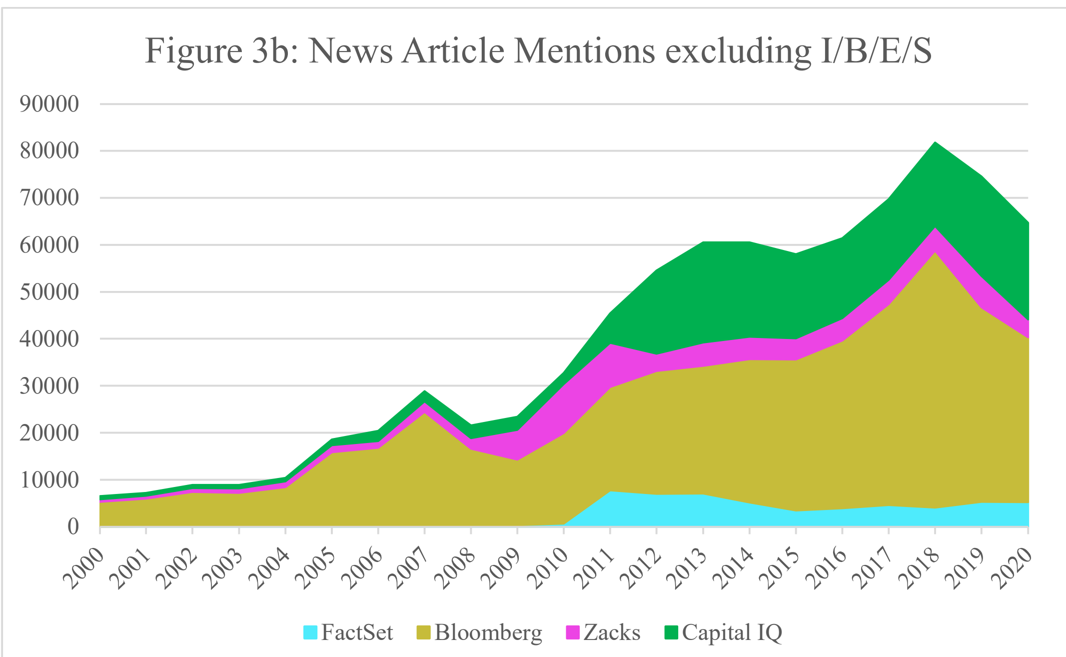
FIGURE 2
Average Number of Contributing Analysts per Available Firm-Quarter by FDP



This figure provides details of the average number of contributing analysts per firm-quarter, where the sample includes the 75,723 firm-quarters contained in the Compustat-CRSP merged file covered by all five forecast data providers, Bloomberg (BB), Capital IQ (CIQ), FactSet (FSET), I/B/E/S (IBES), and Zacks (ZACKS).

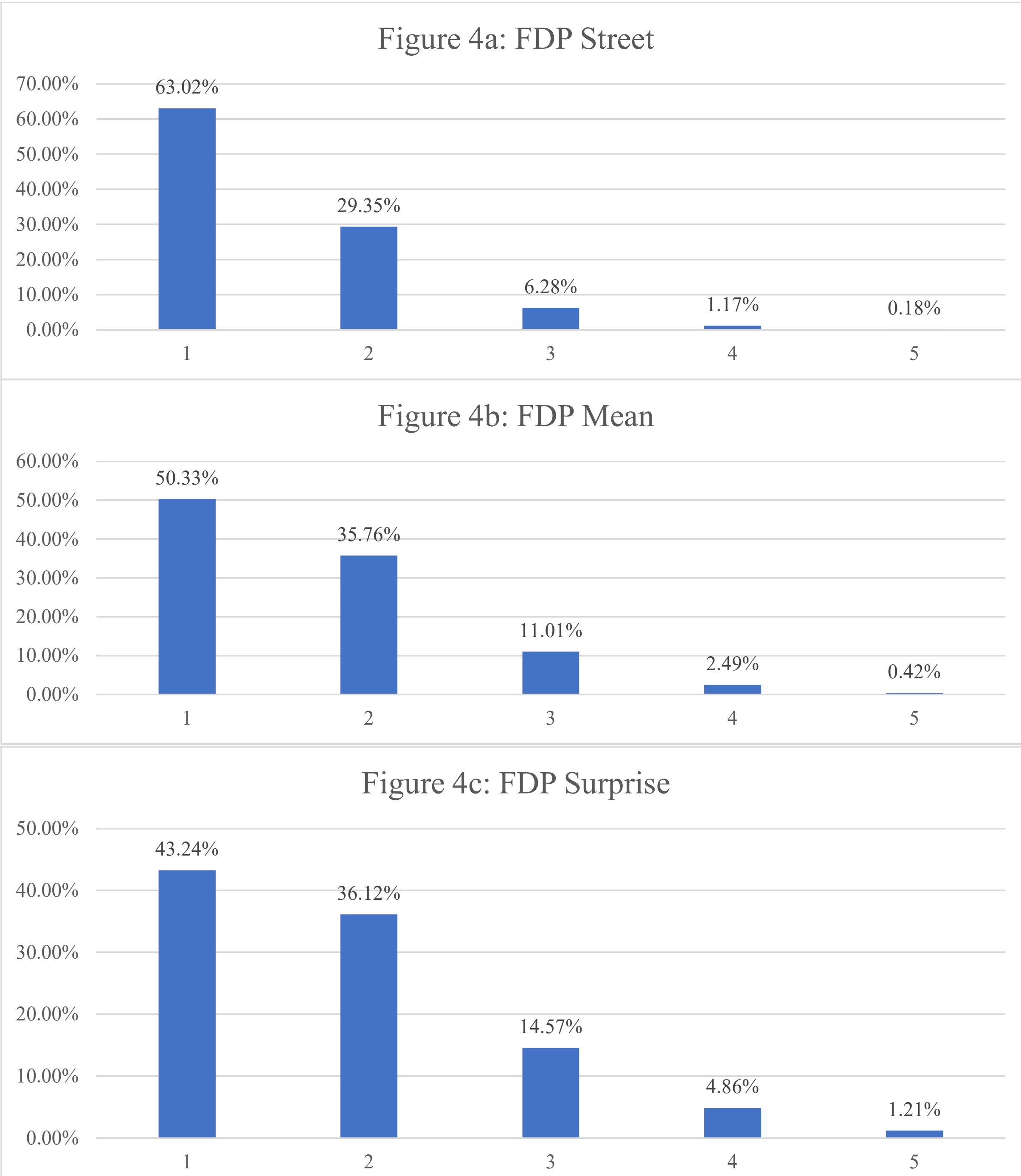
FIGURE 3
Media Citations Per Year





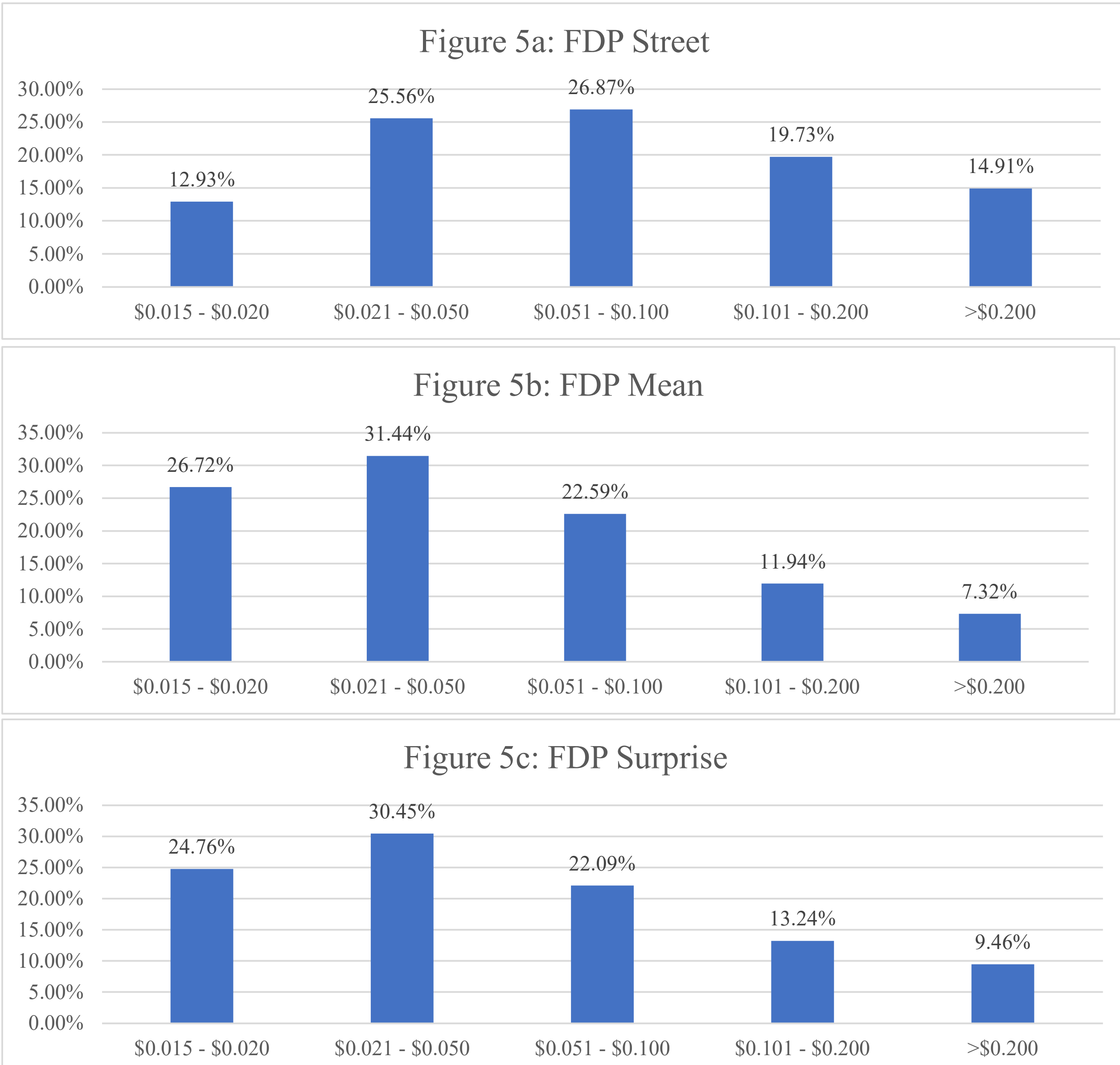
This figure summarizes the number of media citations of each FDP's name and either the word "earnings" or "EPS", according to Lexis-Uni. Specifically, we searched for "EPS and Bloomberg"; or for "EPS and Capital IQ" or "EPS and S&P Capital IQ" or "EPS and S&P Global" or "EPS and McGraw Hill" or "EPS and McGraw-Hill" or "EPS and McGraw Hill Financial" or "EPS and McGraw-Hill Financial" and not "SPGI" (which is the public company that owns S&P Capital IQ); or for "EPS and FactSet" and not "FDS" (which is the public company that owns FactSet); or for "EPS and I/B/E/S" or "EPS and IBES" or "EPS and First Call" or "EPS and Thomson" or "EPS and Reuters" and not "TRI" (which is the public company that owned I/B/E/S during our sample period); or for "EPS and Zacks" or "EPS and Zack's".

FIGURE 4
Number of Unique Values of FDP EPS Data Per Firm-Quarter



This figure provides frequencies of the number of unique values of either street EPS (FDP Street), forecasted EPS (FDP mean), or the FDP surprise (i.e., street less forecasted EPS) provided for each firm-quarter, where the sample includes the 75,723 firm-quarters contained in the Compustat-CRSP merged file covered by all five forecast data providers, Bloomberg, Capital IQ, FactSet, I/B/E/S, and Zacks. Unique values are those that differ by $0.015 or more.

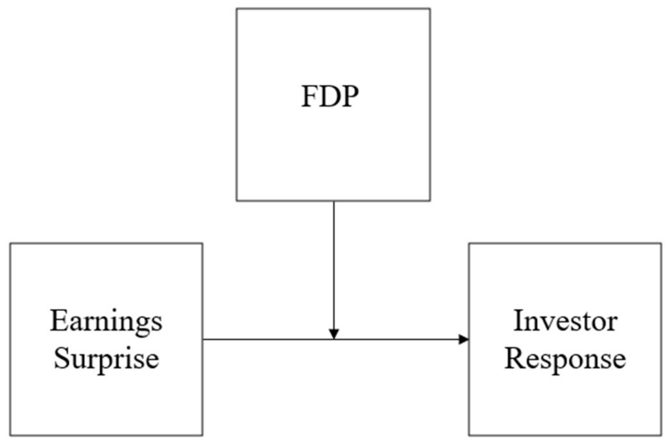
FIGURE 5
Magnitude of FDP Differences



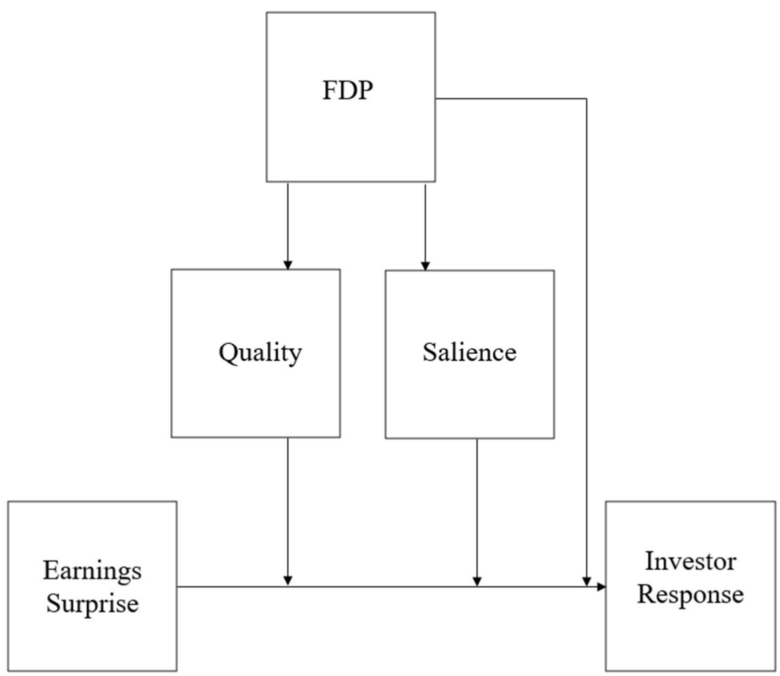
This figure provides the frequency of firm-quarters that fall within a given range of magnitude of FDP differences, in cents per share. In each panel, the sample is restricted to observations with at least two unique values of the specified measure (either FDP street, FDP mean, or the FDP surprise) from the 75,723 firm-quarters contained in the Compustat-CRSP merged file covered by all five forecast data providers, Bloomberg, Capital IQ, FactSet, I/B/E/S, and Zacks. Unique values are those that differ by $0.015 or more. Each column provides the percentage of firm-quarters where the difference between the maximum and minimum value of each measure falls within the range specified below that column. For example, the top left column in the figure illustrates that for 12.93% of firm-quarters in which FDPs disagree about the value of FDP street, the difference between the street EPS from the FDP with the maximum value and the FDP with the minimum value of street EPS for that firm-quarter falls between $0.015 - $0.02 cents per share.

FIGURE 6
Path Analysis

Panel A: FDP Moderation of ERC



Panel B: Quality and Salience Mediating the FDP Moderation of ERC



This figure presents the conceptual model for the relation between the FDP earnings surprise and investors' market reaction described in Section 5.1 of the text. In panel A, this relation is moderated by FDP identity, and in panel B, this FDP moderation effect is further mediated by the quality and salience of FDP earnings information.

TABLE 1
Sample Selection

Panel A: Sample Selection

	Firm-Quarter Observations	FDP-Firm-Quarter Observations
Merged CRSP-Compustat Dataset from 2002 to 2017	327,141	
with non-missing assets, sales, and common equity, and with sales>$25 million and assets > $100 million and price > $1 (*CCM dataset*)	209,035	
with coverage by I/B/E/S	185,045	
with coverage by all five FDPs	96,070	480,350
with control variables	80,196	400,980
truncated sample	75,723	378,615

Panel B: Unique Number of FDPs Covering Each CCM Dataset Firm-Quarter

FDP Coverage	N	%
0	7,494	3.59%
1	15,266	7.30%
2	17,576	8.41%
3	24,317	11.63%
4	48,312	23.11%
5	96,070	45.96%
Total	209,035	100.00%

This table contains details of sample selection in Panel A, and FDP coverage of the CCM dataset of 209,035 firm-quarters by number of different FDPs in Panel B

TABLE 2
Descriptive Statistics

	(1) N	(2) Mean	(3) P50	(4) Std Dev.	(5) P25	(6) P75
<u>FDP Earnings Surprise Differences</u>						
Max Less Min Surp	75,723	0.174	0.047	0.343	0.000	0.165
Std Dev Surp	75,723	0.090	0.031	0.160	0.010	0.091
Miss and Beat	75,723	0.091	0.000	0.287	0.000	0.000
<u>Market Consequences</u>						
MRT	68,417	18.457	21.286	10.251	15.025	25.359
Abnormal Volatility	68,027	0.948	0.920	0.760	0.431	1.438
Abnormal Spread	69,503	0.151	0.131	0.246	-0.006	0.297
Abnormal Depth	69,503	0.075	0.074	0.292	-0.097	0.241
Abnormal Price Impact	69,503	1.416	1.300	0.682	0.962	1.745
CAR	75,723	0.307	0.236	7.888	-3.462	4.179
<u>Explanatory variables</u>						
Unique Following	75,723	3.089	3.000	0.951	2.000	4.000
SBC High	75,723	0.500	0.000	0.500	0.000	1.000
Unexpected Item	75,723	0.425	0.000	0.494	0.000	1.000
abs(Special Items)	75,723	0.336	0.002	1.073	0.000	0.150
abs(ΔShares)	75,723	0.021	0.005	0.061	0.002	0.014
Stock Split	75,723	0.136	0.000	0.342	0.000	0.000
Dispersion	75,723	0.001	0.001	0.002	0.000	0.002
Activation Delay	75,723	3.987	3.526	1.907	2.639	4.890
MVE	75,723	7.656	7.489	1.543	6.503	8.619
BTM	75,723	0.508	0.440	0.345	0.262	0.683
Inst Own	75,723	0.743	0.795	0.220	0.632	0.910
Guidance	75,723	0.240	0.000	0.427	0.000	0.000
abs(ΔIB)	75,723	1.326	0.382	3.423	0.149	0.983
Ret Vol	75,723	0.023	0.020	0.011	0.014	0.028
Q4	75,723	0.244	0.000	0.430	0.000	0.000

This table contains descriptive statistics for the 75,723 firm-quarters in our sample.

TABLE 3
Determinants of FDP Differences

Dependent Variable =	*Max Less Min Surp*	*Std Dev Surp*	*Miss and Beat*
	(1)	(2)	(3)
FDP Methodology Differences			
Unique Following	0.017***	0.008***	0.011***
	(9.29)	(9.22)	(7.52)
SBC High	0.009**	0.007***	0.028***
	(2.49)	(3.83)	(8.87)
Unexpected Item	0.031***	0.015***	0.025***
	(9.14)	(9.18)	(8.29)
abs(Special Items)	0.028***	0.014***	0.016***
	(12.71)	(13.77)	(10.31)
abs(ΔShares)	0.012***	0.006***	0.010***
	(7.61)	(7.63)	(7.12)
Stock Split	-0.004	-0.004	0.008
	(-0.60)	(-1.42)	(1.54)
FDP and Analyst Uncertainty			
Dispersion	0.136***	0.066***	0.040***
	(41.70)	(46.02)	(19.04)
Activation Delay	0.029***	0.014***	0.020***
	(13.11)	(13.71)	(11.44)
Other Firm-Quarter Characteristics			
MVE	-0.037***	-0.020***	-0.010***
	(-14.03)	(-16.07)	(-5.11)
BTM	0.012***	0.005***	-0.002
	(4.19)	(4.13)	(-1.22)
Inst Own	-0.011***	-0.006***	-0.002
	(-4.27)	(-5.26)	(-1.27)
Guidance	0.002	0.005***	-0.004
	(0.36)	(2.68)	(-0.90)
abs(ΔIB)	0.009***	0.006***	-0.000
	(5.87)	(7.58)	(-0.09)
Ret Vol	0.005*	0.005***	-0.005**
	(1.91)	(4.19)	(-2.52)
Q4	0.022***	0.009***	0.008**
	(5.97)	(5.41)	(2.43)
YearQTR FE	Included	Included	Included
N	75,723	75,723	75,723
Adjusted R-squared	0.259	0.284	0.040

TABLE 3 (continued)

This table contains the results of estimating regressions in which the dependent variable represents differences across the five FDPs and the explanatory variables represent FDP methodology differences, FDP and analyst uncertainty, and other firm-quarter characteristics. The dependent variables capture the magnitude of the differences in earnings surprise across the five FDPs (*Max Less Min Surp*, *Std Dev Surp*, and *Miss and Beat*). Intercepts are included but not tabulated. Variable descriptions are in Appendix C. We standardize all independent variables except for indicator variables to have a mean of zero and a standard deviation of one. Significance levels of 10%, 5%, and 1%, are represented by *, **, and *** respectively. T-statistics are reported in parentheses and standard errors are clustered by firm and earnings announcement date.

TABLE 4
Market Consequences of Differences in Earnings Information across FDPs

Panel A: Price Responsiveness

Dependent Variable =		*MRT*	
	(1)	(2)	(3)
Max Less Min Surp	-0.481***		
	(-3.18)		
Std Dev Surp		-1.258***	
		(-3.86)	
Miss and Beat			-0.447***
			(-2.91)
CONTROLS	Included	Included	Included
YearQTR FE	Included	Included	Included
Firm FE	Included	Included	Included
N	68,301	68,301	68,301
Adjusted R-squared	0.078	0.078	0.078

Panel B: Price Volatility

Dependent Variable =		*Abnormal Volatility*	
	(1)	(2)	(3)
Max Less Min Surp	-0.049***		
	(-4.41)		
Std Dev Surp		-0.111***	
		(-4.68)	
Miss and Beat			-0.017*
			(-1.74)
CONTROLS	Included	Included	Included
YearQTR FE	Included	Included	Included
Firm FE	Included	Included	Included
N	67,917	67,917	67,917
Adjusted R-squared	0.232	0.232	0.232

TABLE 4 (continued)

Panel C: Liquidity

Dependent Variable =	*Abnormal Spread*			*Abnormal Depth*			*Abnormal Price Impact*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Max Less Min Surp	-0.002			-0.022***			0.023**		
	(-0.40)			(-4.85)			(2.41)		
Std Dev Surp		0.004			-0.053***			0.047**	
		(0.51)			(-5.24)			(2.23)	
Miss and Beat			0.006			-0.013***			0.016*
			(1.63)			(-3.33)			(1.66)
CONTROLS	Included	Included	Included	Included	Included	Included	Included	Included	Included
YearQTR FE	Included	Included	Included	Included	Included	Included	Included	Included	Included
Firm FE	Included	Included	Included	Included	Included	Included	Included	Included	Included
N	69,394	69,394	69,394	69,394	69,394	69,394	69,394	69,394	69,394
Adjusted R-squared	0.187	0.187	0.187	0.189	0.189	0.189	0.128	0.128	0.128

This table contains the results of estimating regressions in which the dependent variable represents market reaction timeliness (*MRT*) in Panel A, price volatility (*Abnormal Volatility)* in Panel B, and liquidity (*Abnormal Spreads*, *Abnormal Depths*, or *Abnormal Price Impact*) in Panel C. In Panels A through C, the explanatory variables include measures of the magnitude of the differences in earnings surprise across the five FDPs (*Max Less Min Surp*, *Std Dev Surp*, and *Miss and Beat*). We control for *MVE*, *BTM*, *Inst Own*, *Unique Following*, *Guidance*, *Dispersion*, *abs(ΔIB), abs(ΔShares)*, *Stock Split*, *abs(Special Items*), *Ret Vol*, *Activation Delay*, *Q4* and *abs(Surprise)*. We standardize all independent variables except for indicator variables and *Max Less Min Surp*, *Std Dev Surp*, and *Miss and Beat*, to have a mean of zero and a standard deviation of one. Intercepts are included but not tabulated. Variable descriptions are in Appendix C. Significance levels of 10%, 5%, and 1%, are represented by *, **, and *** respectively. T-statistics are reported in parentheses and standard errors are clustered by firm and earnings announcement date.

TABLE 5
FDP-Firm-Quarter Level Descriptive Statistics and Correlations

Panel A: FDP-Firm-Quarter Level Ranks

		IBES	ZACKS	CIQ	BB	FSET
FDP Accuracy	Mean	0.63	0.45	0.58	0.51	0.47
	(Std Dev.)	(0.33)	(0.36)	(0.35)	(0.36)	(0.38)
FDP Predict Op Earn	Mean	0.49	0.48	0.50	0.46	0.46
	(Std Dev.)	(0.39)	(0.40)	(0.40)	(0.41)	(0.41)
FDP Predict Op CF	Mean	0.49	0.47	0.49	0.47	0.47
	(Std Dev.)	(0.39)	(0.40)	(0.40)	(0.41)	(0.41)
FDP Experience	Mean	0.91	0.86	0.48	0.59	0.25
	(Std Dev.)	(0.18)	(0.24)	(0.30)	(0.39)	(0.36)
FDP Agreement	Mean	0.84	0.77	0.83	0.81	0.81
	(Std Dev.)	(0.26)	(0.36)	(0.28)	(0.31)	(0.30)
FDP Media	Mean	0.62	0.57	0.60	0.60	0.61
	(Std Dev.)	(0.47)	(0.47)	(0.47)	(0.47)	(0.47)
FDP Following	Mean	0.86	0.35	0.72	0.65	0.64
	(Std Dev.)	(0.24)	(0.38)	(0.33)	(0.33)	(0.38)

Panel B: Correlations among FDP characteristics

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) *FDP Accuracy*	1.000						
(2) *FDP Predict Op Earnings*	0.054***	1.000					
(3) *FDP Predict Op CF*	0.041***	0.650***	1.000				
(4) *FDP Experience*	0.051***	-0.007***	-0.010***	1.000			
(5) *FDP Agreement*	0.058***	0.075***	0.076***	-0.012***	1.000		
(6) *FDP Media*	0.015***	0.065***	0.066***	-0.019***	0.057***	1.000	
(7) *FDP Following*	0.151***	0.023***	0.026***	0.002	0.093***	0.039***	1.000

This table presents descriptive statistics of the ranked FDP characteristics by FDP and the correlation among them. FDP characteristics include the scaled ranks of historical accuracy (*FDP Accuracy*), historical predictability of the FDP's street earnings for future operating earnings (*FDP Predict Op Earn*) and future operating cash flows (*FDP Predict Op CF*), the number of quarters the FDP has been following the firm (*FDP Experience*), the extent of agreement of the FDP's street earnings with the other four FDPs' street earnings (*FDP Agreement*), the extent of media coverage (*FDP Media*), and the number of individual analysts in the consensus (*FDP Following*). We rank the five FDPs between 0 (lowest) and 4 (highest) within firm-quarter on historical accuracy, historical predictive ability of street earnings for future operating earnings and future operating cash flows, experience, media coverage, and analyst following, respectively, with tied values assigned to the higher rank. We then scale this rank by 4, such that rank ranges between 0 and 1. For agreement, for each firm-quarter we count the number of other FDPs for which the FDP's street EPS agrees within $0.015, which can range from 0 to 4, and scale this number by 4. Panel A shows the mean rank and standard deviation for each FDP and each FDP characteristic. Panel B presents correlations among these variables. Significance levels of 10%, 5%, and 1%, are represented by *, **, and *** respectively.

TABLE 6
Comparison of FDP Earnings Response Coefficients

Dependent Variable =		*CAR*	
	(1)	(2)	(3)
FDP Surprise	2.475***	3.095***	2.689***
	(42.80)	(26.91)	(21.18)
FDP Surprise × ZACKS	-0.046	-0.067**	0.052
	(-1.52)	(-2.22)	(1.64)
FDP Surprise × CIQ	0.024	-0.018	0.004
	(0.75)	(-0.56)	(0.13)
FDP Surprise × BB	-0.143***	-0.176***	-0.036
	(-4.09)	(-4.87)	(-0.90)
FDP Surprise × FSET	-0.318***	-0.313***	-0.150***
	(-9.77)	(-9.80)	(-3.33)
FDP Surprise × FDP Accuracy			0.094***
			(7.05)
FDP Surprise × FDP Predict Op Earn			0.041**
			(2.32)
FDP Surprise × FDP Predict Op CF			0.068***
			(3.68)
FDP Surprise × FDP Experience			0.027
			(1.10)
FDP Surprise × FDP Agreement			0.480***
			(17.57)
FDP Surprise × FDP Media			0.467***
			(6.94)
FDP Surprise × FDP Following			0.030**
			(2.25)
CONTROLS	Excluded	Included	Included
FDP Characteristics	Excluded	Included	Included
MISSING DUMMIES	Excluded	Included	Included
FDP Surprise × CONTROLS	Excluded	Included	Included
FDP Surprise × MISSING DUMMIES	Excluded	Included	Included
N	378,615	378,615	378,615
Adjusted R-squared	0.091	0.115	0.121

TABLE 6 (Continued)

This table contains the results of estimating regressions in which the dependent variable represents the two-day cumulative abnormal return starting on the earnings announcement date (*CAR*). The explanatory variables include the FDP earnings surprise (i.e., FDP street less FDP consensus EPS, scaled by price two days preceding the earnings announcement) (*FDP Surprise*), multiplied by an indicator variable that equals one if the observation represents a given FDP (i.e., *CIQ*, *ZACKS*, *BB*, or *FSET*), and zero otherwise. In this analysis, I/B/E/S is the holdout FDP and thus the coefficient on *FDP Surprise* reflects the estimated earnings response coefficient for I/B/E/S when all other variables interacted with *FDP Surprise* are equal to zero. Other explanatory variables include FDP characteristics (*FDP Characteristics*), which is a vector of variables including *FDP Accuracy*, *FDP Predict Op Earn*, *FDP Predict Op CF*, *FDP Experience*, *FDP Agreement*, *FDP Media*, and *FDP Following*; and the interactions of *FDP Surprise* and each of the variables in *FDP Characteristics*. *CONTROLS* is a vector of variables including *MVE*, *BTM*, *Inst Own*, *Unique Following*, *Guidance*, *Dispersion*, *abs(ΔIB), abs(ΔShares)*, *Stock Split*, *abs(Special Items*), *SBC High*, *Unexpected Item*, *Ret Vol*, *Activation Delay*, *Q4*, and *LnArticles*. *MISSING DUMMIES* is a vector of indicator variables respectively equal to one if FDP historical accuracy, historical predictive ability, or media coverage is missing. We standardize all independent variables except for indicator variables to have a mean of zero and a standard deviation of one. Variable descriptions are in Appendix C. Significance levels of 10%, 5%, and 1%, are represented by *, **, and *** respectively. T-statistics are reported in parentheses and standard errors are clustered by firm and earnings announcement date.

TABLE 7
Path Analysis of FDP Earnings Response Coefficients

	ZACKS		CIQ		BB		FSET	
Direct effect	0.052	(0.042)	0.004	(0.042)	-0.036	(0.041)	-0.150	***(0.044)
Indirect effects:								
FDP Accuracy	-0.035	***(0.005)	-0.006	***(0.001)	-0.024	***(0.003)	-0.038	***(0.005)
FDP Predict Op Earn	0.001	**(0.000)	0.002	**(0.001)	-0.001	**(0.001)	-0.003	***(0.001)
FDP Predict Op CF	-0.001	***(0.000)	0.002	***(0.000)	-0.001	***(0.000)	-0.004	***(0.001)
FDP Experience	-0.004	*(0.002)	-0.025	*(0.013)	-0.026	*(0.014)	-0.040	*(0.021)
FDP Agreement	-0.016	***(0.003)	0.035	***(0.003)	-0.061	***(0.003)	-0.070	***(0.003)
FDP Media	-0.030	***(0.003)	-0.016	***(0.002)	-0.012	***(0.001)	0.008	***(0.001)
FDP Following	-0.034	**(0.016)	-0.016	**(0.007)	-0.015	**(0.007)	-0.016	**(0.007)
Total Effect	**-0.067**		**-0.018**		**-0.176**		**-0.313**	

This table reports the coefficient estimates from a mediated moderation path analysis of the relation between the FDP earnings surprise (*FDP Surprise*) and the two-day cumulative abnormal return starting on the earnings announcement date (*CAR*). The moderators are indicator variables that equal one if the observation represents a given FDP (i.e., *CIQ*, *ZACKS*, *BB*, or *FSET*), and zero otherwise, and the mediators are FDP characteristics, including *FDP Accuracy*, *FDP Predict Op Earn*, *FDP Predict Op CF*, *FDP Experience*, *FDP Agreement*, *FDP Media*, and *FDP Following*. Following Kwan and Chan [2018], we use structural equation modelling to estimate the direct, indirect, and total effects of each FDP's moderation effect on the relationship between *FDP Surprise* and *CAR,* as described in detail in Appendix D. Control variables are included in all model equations as specified in equation (3) and Appendix D, but not reported. Variable definitions are provided in Appendix C. Significance levels of 10%, 5%, and 1%, are represented by *, **, and *** respectively. Nonparametric bootstrapped standard errors (based on 1,000 resamples) are reported in parentheses.