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Analyst Research Activity During the COVID-19 Pandemic

This paper documents that, in response to the COVID-19 pandemic, analysts increase their research activity and significantly revise their forecasts when compared to the pre-pandemic period. Uncertainty-adjusted forecast errors are either comparable or smaller during the pandemic compared to the pre-pandemic period. Investor attention and price reactions to analyst forecast revisions are higher during the pandemic and the effect is stronger in periods where investors actively search for information about firms. During the pandemic, investors value analyst price discovery role more than their role in interpreting public information. Jointly, the results suggest that analysts play an important information intermediation role during the COVID-19 pandemic.

Key words: COVID-19; Coronavirus; Analysts; Forecast accuracy; Price reactions; Information discovery; Information intermediation.

Moyer *et al.* (1989, p. 503) highlight that 'analysts play [...] an important role in making the security markets more efficient' by informing investors' decisions regarding how to allocate their capital (Fama and Jensen, 1983). Analysts fulfil this role through independent research on companies, which includes an analysis of the firm's value and prospects, which they share with investors through their reports. Analyst research should be particularly valuable to investors during periods of severe and unexpected market shocks, such as the COVID-19 pandemic, where investors face significant uncertainty about firms' prospects. However, for two reasons, it is unclear how analysts have responded to the COVID-19 pandemic shock and whether they were able to produce informative research during this time.

First, Baker *et al.* (2020) highlight that no other crisis has had such a sudden and market-wide impact. The origin of the pandemic, the global spread of the coronavirus, and the channels through which it has affected firms and analysts are unique and different compared to the effects of cyclical macroshocks.[1] Greenwood

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[1] The COVID-19 pandemic restricts consumers' ability to purchase products during lockdowns—a demand shock—and firms' ability to supply their products—a supply shock. It also curbs analysts' ability to acquire information, for example, from managers; work in their familiar environment; and learn from other firms and peers.

et al. (2022, p. 863) document that economic crises, including the 2007 financial crisis, are predictable; they argue that their 'evidence challenges the view that financial crises are unpredictable "bolts from the sky" and supports the Kindleberger-Minsky view that crises are the byproduct of predictable, boom-bust credit cycles'. If financial crises are predictable, analysts can use past knowledge to understand when a financial crisis is likely to take place and how it will affect firms' behaviour. The COVID-19 pandemic is a unique realization of a market-wide tail-risk shock, offering an opportunity to study analysts' research activity in response to an unexpected macroeconomic shock.[2]

Second, it is not clear how the COVID-19 pandemic has affected analyst research activity. On the one hand, the surge in uncertainty due to the pandemic should increase investor demand for information that helps them assess firm fundamentals and value, which in turn should incentivize analysts to exert effort, and increase the frequency and usefulness of their reports (Grossman and Stiglitz, 1980; Bloom, 2009; Pastor and Veronesi, 2012; Amiram *et al.*, 2018). The increase in demand for analyst research should come from both institutions that do not have buy-side research departments and institutions with buy-side desks as 'buy-side analysts are an important consumer of sell-side research' (Brown *et al.*, 2015, p. 140).[3] Analysts may have uncovered new information during the pandemic by better anticipating how the COVID-19 regulation, for example, about lockdowns and government financial support, is likely to affect firms and customers, and by observing the behaviour of similar firms across states or countries. Hutton *et al.* (2012) compare the accuracy of analyst and management forecasts and conclude that analysts' information advantage lies at the macroeconomic level. Further, analysts can gain information from management conference calls (Hassan *et al.*, 2021) and are better able to analyze firm disclosures than investors (Livnat and Zhang, 2012) even when lockdowns reduce the opportunity for private meetings with managers, for example, through corporate site visits. Analyst forecasting experience can also help them better anticipate more persistent earnings, resulting in superior forecasts. For example, Cui *et al.* (2021) report that Chinese firms with higher conditional conservatism performed better during the COVID-19 pandemic. Analysts are incentivized to

[2] Tail risk is the chance of an abnormally large loss in firm value due to a rare event as predicted by the probability distribution. Traditionally, tail risk reflects the chance that investment value will move more than three standard deviations from the mean (Kelly and Jiang, 2014). The quick spread of the coronavirus coupled with the uncertainty regarding how consumers, governments, and firms would respond to the pandemic resulted in a sudden and market-wide increase in uncertainty. To illustrate, between 19 February and 23 March 2020, the S&P 500 stock market index lost 33.7%, then surged by 29% between 24 March and 17 April. High volatility continued after the first quarter of 2020.

[3] Brown *et al.* (2015, p. 140) note several ways through which sell-side analysts add value to buy-side analysts. First, 'buy-side analysts typically follow more companies spread across more industries than do sell-side analysts, so they often rely on the sell side to quickly get up to speed on a particular industry. Further, buy-side analysts indicate that industry knowledge is the most useful input to their stock recommendations, which are the primary determinants of their compensation'. Brown *et al.* (2015) highlight that their findings help explain why institutional investors consistently rate industry knowledge so highly in institutional investors' annual rankings of sell-side services.

respond to institutional demand for their research and produce informative research because their compensation depends on buy-side clients' votes (Groysberg *et al.*, 2011). Past studies highlight that increased institutional demand for analyst research increases the frequency and quality of analyst reports (Bhushan, 1989; O'Brien and Bhushan, 1990; Ackert and Athanassakos, 1997; Das *et al.*, 1998). The increase in investor demand for analyst research is likely to have been compounded by a decrease in firms' voluntary disclosures during the pandemic (Aaron *et al.*, 2021) caused by the unprecedented shock to firms' earnings and cash flows, and real economic activity, for example, supply chain constraints (Baker *et al.*, 2020; Ding *et al.*, 2020).[4]

On the other hand, the unique nature of the COVID-19 shock means that analysts have no prior experience to guide their analysis leading to potentially noisy and uninformative research. Lockdowns and social distancing also restrict analysts' ability to acquire information through face-to-face meetings with colleagues and managers of firms they follow, which could result in lower-quality outputs. To protect their reputation, analysts may reduce their research production rather than issue low-quality forecasts (Ertimur *et al.*, 2011). The financial strain on brokerage houses could also reduce analysts' rewards, leading to lower analyst motivation for accurate and informative research (Loh and Stulz, 2018). Thus, how the COVID-19 pandemic has affected analyst research activity and the usefulness of their reports is an open question that I tackle empirically.

Compared to earlier research which is focused on macroeconomic shocks and analyst research, focusing on the COVID-19 pandemic has important econometric benefits. The COVID-19 pandemic is exogenous to firm and analyst characteristics; thus, changes in properties of analyst forecasts cannot be explained by omitted correlated variables. In contrast, the exogeneity of economic downturns cannot be ascertained as these, by definition, are associated with gradually deteriorating corporate fundamentals. Thus, the COVID-19 pandemic setting is free of typical endogeneity concerns plaguing accounting research making it a natural laboratory to reliably study analyst behaviour and the informativeness of their research forecasts in response to unexpected market shocks.

I collected a sample of 644,630 quarterly earnings-per-share (EPS) forecasts issued between January 2018 and March 2022 for 5,899 unique firms. I classify forecasts issued from January 2020 to March 2022 as pandemic forecasts because (1) Baker *et al.* (2020, p. 748) highlight that the 'the COVID-19 volatility surge began in the fourth week of January' and (2) the Q1 results for 2020 will have been affected by the pandemic, forcing analysts to incorporate its effect into their

[4] It is unlikely that during the COVID-19 pandemic institutions with buy-side desks would rely only on their buy-side analyst research. Previous research documents significant value of sell-side compared to buy-side analyst research. For example, Groysberg (2008, p. 25) report that 'analysts at the buy-side firm made more optimistic and less accurate forecasts than their counterparts on the sell side', and Hobbs and Sing (2015) report that sell-side analysts outperform buy-side analysts in terms of profitability of their reports. Thus, institutions with buy-side desks are likely to use sell-side analyst research to inform their investment decisions. Importantly, not all institutions have in-house buy-side desks and these institutions would use sell-side analyst research.

forecasts.[5] I consider forecasts issued between January 2018 and December 2019 as pre-pandemic forecasts. To understand how the pandemic has affected the *breadth* of analyst research, I also collected quarterly revenue estimates (SAL), cash flow-per-share forecasts (CPS), and dividend-per-share estimates (DPS) issued jointly with EPS forecasts. I look at revenue forecasts following the evidence in Ertimur *et al.* (2011), that is, investors use revenue estimates to disaggregate earnings forecasts into revenue and cost estimates and attach more weight to the more persistent revenue component. Cash flow forecasts help investors to disaggregate earnings estimates into accrual and cash flow estimates allowing them to gauge earnings persistence and the likelihood of financial distress (DeFond and Hung, 2003; Givoly *et al.*, 2009). Dividend forecasts assess future payouts and contain incremental information compared to earnings, revenue, and cash flow estimates and help investors assess persistence of earnings (Bilinski and Bradshaw, 2022). In testing the informativeness of forecast revisions, I also look at analyst target prices and stock recommendations, which reflect an analyst's investment advice.

I first examine changes in the supply of analyst forecasts in response to the COVID-19 pandemic. I find that, compared to the same pre-pandemic months, the number of quarterly EPS estimates is similar in January and February 2020, increases by 72% in March 2020, and remains higher at around 14% between April and December 2020. Analyst research activity converges to pre-pandemic levels between Q1 2021 and Q1 of 2022. Similar patterns are evident for other forecasts analysts supply. Specifically, compared to the same pre-pandemic months, the number of revenue forecasts, cash flow forecasts, and dividend estimates increase in March 2020 by 80%, 75%, and 47% respectively. The number of target prices is 154% higher and stock recommendations are 88% higher in March 2020 compared to same month before the pandemic. The issuance of other forecasts converges to pre-pandemic levels towards the latter period of the pandemic. Thus, analysts' initial response to the pandemic-induced market uncertainty was to increase the quantity of EPS forecasts and the breadth of their research.

Next, I examine forecast errors. The average EPS forecast error increases by 76% for Q1 2020 results compared to Q1 before the pandemic and reduces gradually to a 19% higher error in Q1 2022. Compared to the pre-pandemic period, revenue forecast error is on average 43% higher during the pandemic, cash flow forecast error is up by 17%, and dividend forecast errors are on average 16% higher. Thus, research production during the pandemic is associated with lower average precision of estimates measured in standard ways. However, Loh and Stulz (2018, p. 961) argue that 'traditional measures of analyst precision are not appropriate for comparing precision across good and bad times. Rather, a relevant measure of precision is one that takes into account the underlying uncertainty'. When I calculate uncertainty-adjusted forecast errors following Loh and Stulz (2018), I find that forecast errors per unit of uncertainty are either comparable or smaller during the pandemic compared to the pre-pandemic levels,

[5] My conclusions are the same if I had designated the start of the pandemic as the beginning of March 2020.

but for Q1 of 2020. Thus, the quality of uncertainty-adjusted forecasts issued during the pandemic, after the initial shock, is higher than that of the pre-pandemic period.

Next, I turn to investor assessment of the informativeness of analyst research as measured by (1) Bloomberg's News Heat Average Readership Score to capture institutional attention (Ben-Rephael *et al.*, 2017) and (2) price reaction regressions. I focus on institutional attention because Ben-Rephael *et al.* (2017, p. 3009) highlight that '[I]nformation needs to attract investor attention before it can be processed and incorporated into asset prices via trading'; thus, documenting that analyst forecasts attract investor attention to the firm helps us understand why investors trade on analyst forecasts.[6] I then focus on price reactions to examine if analyst revisions reveal valuable new information during the COVID-19 pandemic that investors use to guide their investment decisions (Stickel, 1995; Womack, 1996).

I document three results. First, compared to the pre-pandemic period, there are significant revisions in all analyst forecasts in 2020: the absolute magnitudes of analyst revisions are 81% higher for EPS forecasts, 114% higher for revenue estimates, 51% higher for cash flow forecasts, and 68% higher for dividend estimates. I also observe 10% stronger recommendation revisions and 60% higher absolute price target revisions. The average absolute revisions are comparable to pre-pandemic levels in the latter part of the pandemic. Thus, analysts significantly revise their forecasts during the pandemic, particularly at its onset.

Second, regression analysis shows that institutional attention, as measured by Bloomberg news searches, is higher around analyst forecast announcements during the pandemic compared to the pre-pandemic period. These results are consistent with the Bayesian framework (e.g., Pastor and Veronesi, 2012), that is, as the accuracy of analyst signals relative to underlying firm uncertainty increases, investors put more weight on these signals. This evidence is also consistent with the relatively higher importance of analyst research when managers reduce their voluntary communication, as happened during the pandemic (Aaron *et al.*, 2021).

Third, I confirm incrementally significant price reactions to analyst forecast announcements during the pandemic compared to the pre-pandemic period.[7] The economic effects are large, for example, price reactions to EPS forecast revisions are on average 83% higher during the COVID-19 pandemic compared to the pre-pandemic period. These conclusions are robust to alternative measures of price reactions, of analyst forecast revisions, and to including firm-fixed and analyst-fixed effects in the model.

[6] BenRephael *et al.* (2017, p. 3010) argue that Bloomberg terminals are used primarily by institutional investors and the most common job titles of Bloomberg users 'include portfolio/fund/investment managers, analyst, trader, executive, director, president, and managing director'. We examine institutional attention rather than retail attention, which is more commonly captured by Google searches because institutional ownership has accounted for more than 80% of common equity ownership in the US since the second half of 2000s (Stambaugh, 2014).

[7] The regressions exclude a three-day window around quarterly earnings announcements as analyst revisions in those periods can piggyback on firm information releases (Zhang, 2008; Altinkilic and Hansen, 2009).

To shed more light on *why* investors put more weight on analyst forecasts during the pandemic, I perform two tests. First, I examine the role analyst research plays in resolving uncertainty during periods of increased investor demand for information. I capture information demand by the intensity of (i) Bloomberg terminal searches for firm information, (ii) Google searches for the pandemic and for stock market information, and (iii) the variation in voluntary corporate disclosure.[8] I find that price reactions to analyst forecast revisions during the COVID-19 pandemic are incrementally higher during periods of increased investor information demand. This result is consistent with analysts responding to higher investor information demand during the COVID-19 pandemic, which helps to explain incrementally higher price reactions to analyst forecast announcements during this period.

Second, I examine whether investors value the analyst private information discovery role more than their role in interpreting corporate information during the pandemic. Chen *et al.* (2010) document that information discovery dominates in the weeks *before* firms announce their earnings results and information interpretation is more important in the weeks *after* earnings announcements. I follow Chen *et al.* (2010) and focus on analyst EPS forecasts issued in a 10-day window around earnings announcements excluding a three-day window centered on the earnings announcement day to avoid confounding effects. I find that during the pandemic, investors value the analyst private information discovery role more than their role in interpreting public information, a result that is consistent with greater demand for new information during this period.

This study offers several contributions to the literature. First, it contributes to the accounting literature that examines the capital markets consequences of analyst research. This literature has examined the accuracy and price impact of analyst forecasts, and the importance of the analyst information discovery role compared to their role in interpreting public information (Dempsey, 1989; Shores, 1990; Womack, 1996; Loh and Stulz, 2011; Ivkovic and Jegadeesh, 2004; Chen *et al.*, 2010). I document how the COVID-19 pandemic, an unexpected macroeconomic shock, has affected analyst research production, accuracy of forecasts, and investor assessment of analyst research information content. My findings suggest that analysts' information intermediation role during periods of high market uncertainty, such as the COVID-19 pandemic, has significant value. This evidence contrasts with views on the declining importance of sell-side analysts in the market stemming from regulatory changes, such as the Markets in Financial Instruments Directive II in Europe (Fang *et al.*, 2020); declining research budgets; and an increasing shift to passive ownership (Appel *et al.*, 2016).[9]

8 See Da *et al.* (2011) for tests validating Google searches as an information demand measure. Bento *et al.* (2020) document a 36% spike in Google searches for information following public announcements of COVID-19 cases. Costola *et al.* (2020) report that Google searches are associated with stock price volatility in a cross-section of six countries.

9 Bloomberg highlights that 'Research is the niche that's been buffeted most violently by the forces crashing into the finance industry: technology, regulation and the demands of the marketplace itself' and 'Research spending by the buyside has dropped between 20% and 30% since the new rules [MiFID II] came in' (Lee, 2019).

The present paper's evidence on how the COVID-19 pandemic has affected analyst research activities sheds light on the analyst's role as an information producer. Previous research provides conflicting results on the analyst information discovery role. Early research based on price reactions to analyst forecast announcements suggests that they reveal valuable new information (Stickel, 1995; Mikhail *et al*., 2004). In contrast, Altinkilic and Hansen (2009) argue that most analyst stock recommendation revisions come closely after corporate news and that the evidence of price reactions to recommendation revisions is attributable to preceding corporate news. They conclude that analysts piggyback on public information to better align their recommendation revisions with recent and future returns, which 'can improve analyst stock picking reputation and spur trading, boosting brokerage revenues and analyst income, and reducing the chance of jobloss' (Altinkilic and Hansen, 2009, p. 18). Such piggybacking is less possible during the pandemic as managers significantly reduce voluntary disclosure (Aaron *et al*., 2021) and corporate disclosure is less informative (Wang and Xing, 2020). The present research adds novel evidence to the debate on the information production role of analysts in high uncertainty periods with scarce corporate disclosures.[10]

Second, I provide new insights to the literature that examines the value of analyst research in economic downturns, which so far has produced mixed results. Loh and Stulz (2018) report that in bad times, captured by market recessions, analysts produce more informative research. In contrast, Amiram *et al.* (2018) argue that when market uncertainty is high, timeliness and forecast accuracy decline. Chen *et al.* (2020, p. 333) document that 'macro uncertainty measures are significantly and negatively correlated with the accuracy and informativeness of analysts' earnings forecasts and positively correlated with the dispersion of earnings forecasts', and Hope and Kang (2005), Baloria and Mamo (2017), and Arand and Kerl (2012) report similar evidence. Focusing on bias, Kretzmann *et al.* (2015, p. 49) report that 'in recessions sell side analysts are too optimistic about the stocks they recommend to buy', but Richards *et al.* (1977) document that EPS forecasts issued during booms tend to be overly optimistic while forecasts issued during busts are less optimistic. Dreman and Berry (1995) find no difference in optimism in EPS forecasts between expansions and recessions. Economic recessions are cyclical, predictable, and persistent (Stock and Watson, 1989; Estrella and Mishkin, 1998; Kaupp and Saikkonen, 2008), thus they are associated with a very different forecasting challenge than a tail-risk event such as the COVID-19 shock. My focus on the tail-risk event related to the

[10] On 4 March 2020, the SEC issued an order providing conditional regulatory relief and assistance to reporting companies impacted by the coronavirus. The order gives companies an additional 45 days to file certain Exchange Act reports (including Form 10-K and Form 10-Q) otherwise due between 1 March 2020 and 30 April 2020 if they satisfy certain conditions. https://www.sec.gov/news/press-release/2020-74

COVID-19 pandemic provides novel evidence on how the informativeness of analyst research changes in response to an unexpected market shock.[11]

Third, I add to the growing literature on the impact of the COVID-19 pandemic on financial markets. Du (2020) uses analyst forecasts issued in March 2020 to examine the timeliness of forecasts by female compared to male analysts. Landier and Thesmar (2020) use earnings forecasts to infer the implied discount rates for the largest NYSE, Nasdaq, or Amex stocks during the COVID-19 crisis. Cox *et al.* (2020) estimate a dynamic asset pricing model to capture fluctuations in the pricing of stock market risk during the pandemic. Ding *et al.* (2020) study firm characteristics that predict the magnitude of share price drop in response to the COVID-19 outbreak. Baker *et al.* (2020) document the dynamics of news about the disease between February 2020 and April 2020, and their correlation with the stock market volatility. Ramelli and Wagner (2020) examine the magnitude of price declines during the pandemic. Li *et al.* (2021) report that firms with a strong corporate culture outperform peers with a weak culture during the pandemic. Cejnek *et al.* (2020) study the effect the COVID-19 pandemic has had on corporate dividend policy, Anginer *et al.* (2020) look at its effect on insider trades, and Tkachenko and Bataeva (2020) examine its impact on share repurchases. Fahlenbrach *et al.* (2020) study the effect financial flexibility has had on share price reactions to the COVID-19 outbreak. The evidence in the present paper showcases analysts' response to the COVID-19 pandemic.

DATA

I collected analyst individual quarterly EPS forecasts and contemporaneously issued quarterly revenue, cash flow, and dividend estimates, target prices and stock recommendations from I/B/E/S over the period January 2018 to March 2022. I/B/E/S imposes a four-month gap between when the data are available for academic compared to commercial research, which determines the end of my sample period. I require that the forecasts have the actual value to calculate forecast errors and share price information on CRSP. The final sample includes 644,630 EPS forecasts issued for 5,899 unique firms by 3,906 unique analysts employed by 318 unique brokers.

Table 1 presents the annual number of forecasts between 2018 and Q1 of 2022. There are a comparable number of EPS forecasts issued in 2018 and 2019, a

[11] Indirectly, the study also contributes to the literature on stock price crash risk. Studies that examine the determinants of stock price crash risk focus on firm-specific risk purged of market-wide factors, which is conceptually different from my focus on the impact of a market-wide event (Chen *et al.*, 2001; Jin and Myers, 2006; Hutton *et al.*, 2009; Kim and Zhang, 2014). Further, similar to the literature on macroeconomic shocks, the literature on crash risk has focused on its determinants, as studying consequences suffers from the inherent endogeneity problem. Habib *et al.* (2017, p. 212) survey the literature on the determinants and consequences of stock price crash risk and conclude that '[D]espite a proliferation of crash risk research over the last seven to 8 years, there is very little research on the consequences of crash risk'. The exceptions are An *et al.* (2015), who examine the speed of leverage adjustment following a crash risk, and Wu (2013), who reports that CEO turnover increases in the year after crash risk.

TABLE 1

THE ANNUAL DISTRIBUTION OF ANALYST FORECASTS

	2018	2019	2020	2021	Q1 2022	Total
Earnings forecasts (EPS)	150,122	146,060	164,741	147,017	36,690	644,630
Revenue forecasts (SAL)	102,430	101,232	117,122	103,689	26,249	450,722
% of EPS forecasts	68.23%	69.31%	71.09%	70.53%	71.54%	69.92%
Cash flow forecasts (CPS)	22,443	19,951	19,637	16,145	3,843	82,019
% of EPS forecasts	14.95%	13.66%	11.92%	10.98%	10.47%	12.72%
Dividends forecasts (DPS)	6,446	6,108	6,159	5,421	1,762	25,896
% of EPS forecasts	4.29%	4.18%	3.74%	3.69%	4.80%	4.02%
Target prices (TP)	65,370	62,752	80,957	69,262	17,344	295,685
% of EPS forecasts	43.54%	42.96%	49.14%	47.11%	47.27%	45.87%
Stock recommendations (REC)	10,778	9,987	11,379	10,392	2,212	44,748
% of EPS forecasts	7.18%	6.84%	6.91%	7.07%	6.03%	6.94%

This table reports the annual number of analyst quarterly earnings-per-share forecasts (EPS), revenue forecasts (SAL), cash flow-per-share forecasts (CPS), dividend-per-share forecasts (DPS), target prices (TP), and stock recommendations.

significant increase in 2020, and subsequent reversal in 2021. The average fraction of revenue forecasts issued with EPS estimates is 69.92%, a result that is consistent with Ertimur *et al.* (2011) and Bilinski and Eames (2019), that is, since 2001, almost all analysts produce revenue estimates. I find that 12.72% of EPS forecasts are issued jointly with cash flow forecasts, which is twice the fraction of joint EPS and cash flow forecasts reported in DeFond and Hung (2003) for their period 1993–1999 and higher than 9.3% in Bilinski (2014) over the period 2000–2008. Around 4.02% of EPS estimates are issued jointly with a dividend forecast, evidence that is consistent with Bilinski and Bradshaw (2022), that is, dividend forecasts are rare in the US. Target prices are issued with 45.87% of earnings forecasts, and stock recommendations with around 6.94% of EPS estimates.

EMPIRICAL RESULTS

Changes in the Supply of Analyst Forecasts During the Pandemic

The first test examines changes in the monthly number of analyst forecasts during the pandemic compared to similar periods before the COVID-19 outbreak. This test is useful to understand the analyst supply response to the outbreak of the pandemic. Figure 1 plots the monthly number of quarterly EPS forecasts in the pre-pandemic years 2018 and 2019 and during the pandemic period 2020 to Q1 of 2022. I identify three main results. First, Figure 1a shows that the number of EPS forecasts is markedly similar in 2018 and 2019, which suggests a routine in analyst research production.[12] Second, Figure 1b shows that there is a significant increase in the number of earnings forecasts in March 2020 compared to March 2021 and

[12] I cannot reject the null that the number of forecasts each month is similar between 2018 and 2019.

FIGURE 1

DISTRIBUTION OF EPS FORECASTS PER FIRM-YEAR-MONTH BEFORE AND DURING THE COVID-19 PANDEMIC

This figure reports the monthly number of analyst earnings forecasts issued between January 2018 and March 2022.

March 2022—March 2020 is the month that observed the most dramatic increase in volatility. This result suggests that analysts promptly responded to the pandemic by updating their forecasts. The number of EPS forecasts towards the end of 2020 is comparable with Q1 of 2021 suggesting a mean reversion in analyst research activity in later periods. Third, comparing the number of EPS forecasts issued during the pandemic compared to the pre-pandemic period in Figure 1c, we observe a spike in the early months of the pandemic (March to May) and a convergence to pre-pandemic levels over subsequent months. The overall picture from Figure 1 is that of a significant supply response by analysts to the onset of the pandemic and a subsequent mean reversion to pre-pandemic research activity in later periods.

To dig deeper, Figure 2 examines changes in (1) analysts' coverage of firms during the pandemic compared to the pre-pandemic period, (2) the average number of firms an analyst covers, (3) the breadth of analyst research, and (4) the number of analysts covering a firm. Figure 2a documents that during the COVID-19 pandemic analysts provide EPS forecasts for a larger number of firms and Figure 2b shows that an average analyst covers a slightly larger number of firms. Figure 2c reports an increase in the proportion of EPS forecasts issued with another forecast (either a revenue forecast, cash flow forecast, dividend forecast, target price, or a stock recommendation). Analysts increase the breadth of their research as they are more likely to supplement their earnings forecasts with other estimates. To follow up on this result, Appendix A documents a significant increase in the availability of revenue, cash flow, and dividend forecasts, particularly in the early months of the pandemic, and convergence to pre-pandemic levels in the latter part of the pandemic. Specifically, compared to the same pre-pandemic month, the number of revenue forecasts, cash flow forecasts, dividend estimates, target prices, and stock recommendations increases by 80%, 75%, 47%, 154%, and 88% respectively.

It is plausible that some analysts stopped coverage after the start of the pandemic and the evidence in Figure 1a reflects an increased research production by a subsample of analysts. Figure 2d reports the monthly number of analyst–firm pairs over the pre-COVID-19 and the pandemic months. I do not find evidence that the average number of analysts covering a stock reduces during the pandemic. To formally test that the average coverage during the pandemic is similar to the pre-pandemic years, I calculate the average persistence in coverage between 2018 and 2019 and then between 2019 and 2020. On average, 78.5% of analysts covering a stock in 2018 also cover that stock in 2019. Around 92.7% of analysts who cover a firm in 2019 also cover that firm in 2020. The persistence between 2020 and 2021 is 90.3%. The chi-square test for the significance in the proportions is not significant (result untabulated). This evidence suggests similar coverage between pre-pandemic and pandemic years.[13] Overall, the evidence in Figures 1 and 2 is consistent with analysts promptly responding to the onset of market uncertainty caused by the pandemic shock by increasing their stock coverage and the quantity and depth of their research.

[13] I also looked specifically at coverage in the travel, tourism, and hospitality industries, which have been most affected by COVID-19, but did not find evidence of reduced analyst coverage during the COVID-19 pandemic in those industries.

FIGURE 2

CHARACTERISTICS OF ANALYST COVERAGE BEFORE AND DURING THE COVID-19 PANDEMIC

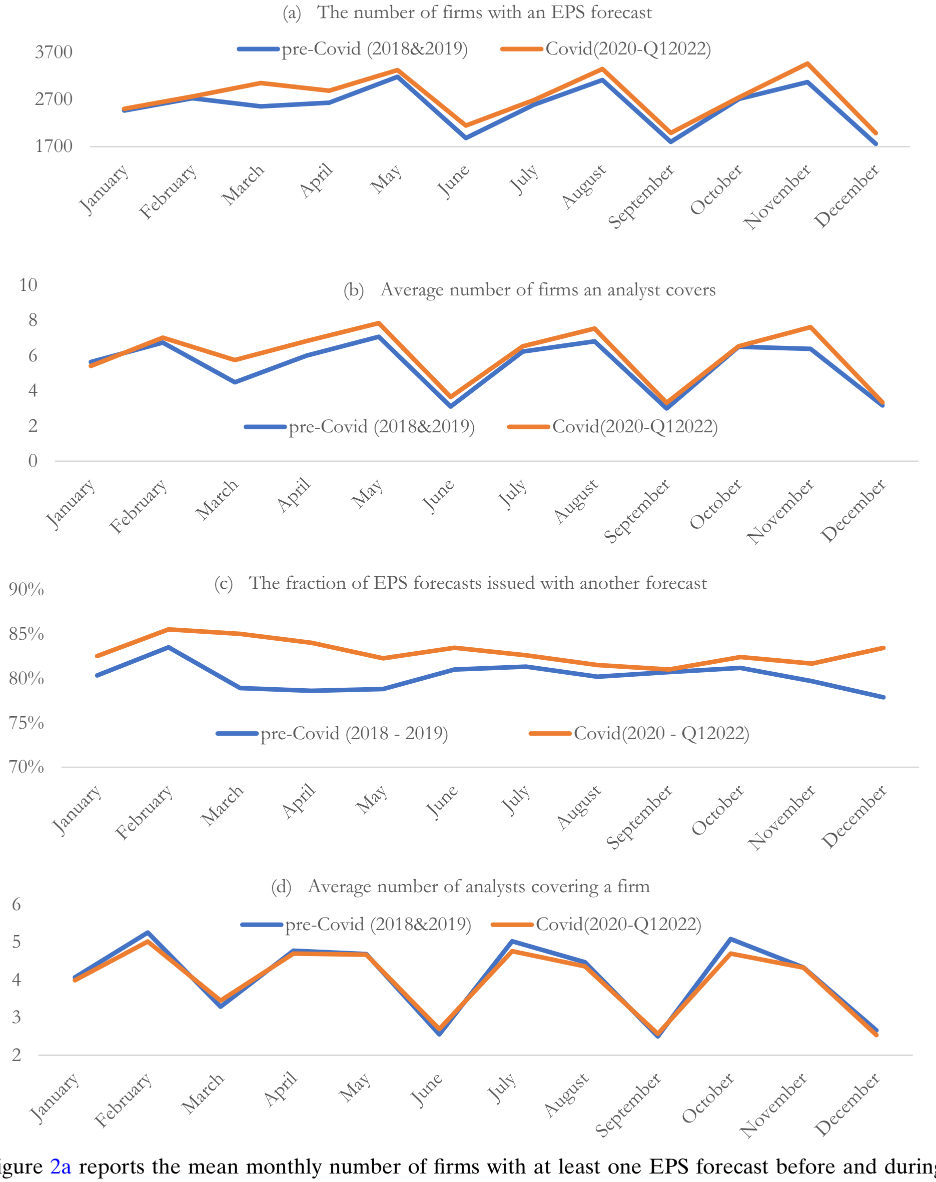
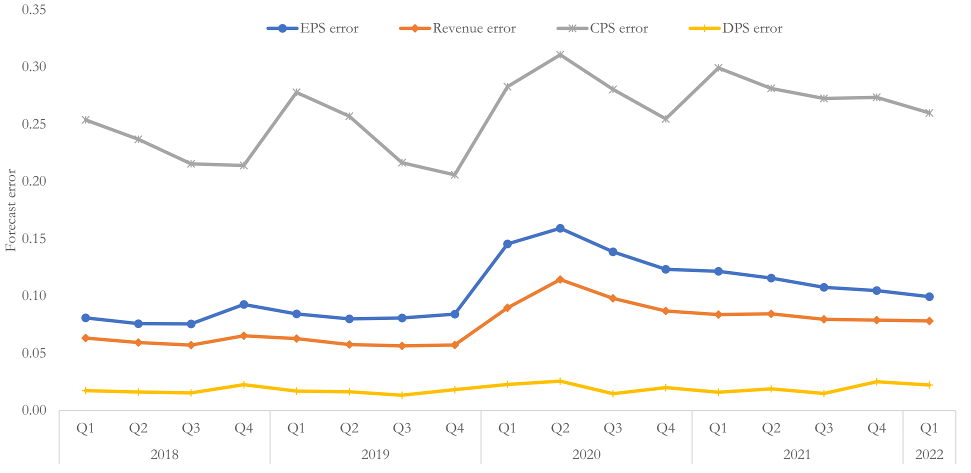


Figure 2a reports the mean monthly number of firms with at least one EPS forecast before and during the COVID-19 pandemic. Figure 2b reports the average number of firms an average analyst covers. Figure 2c reports the proportion of EPS forecasts issued jointly with either a revenue forecast, cash flow forecast, dividend forecast, target price, or a stock recommendation. Figure 2d reports the average number of analysts issuing forecasts for an average firm.

FIGURE 3

QUARTERLY FORECAST ERRORS FOR ANALYST EARNINGS, REVENUE, CASH FLOW, AND DIVIDEND FORECASTS



This figure reports the average quarterly percentage forecast error for analyst earnings, revenue, cash flow, and dividend forecasts. Forecast error is calculated as the absolute difference between the actual and forecasted values, scaled by one plus the absolute value of the actual value.

Forecast Accuracy

Next, I examine the accuracy of analyst earnings, revenue, cash flow, and dividend forecasts. Because the forecasts I use are on a per-share and non-per-share basis, I require measures of forecast error that are scale-independent. Following Hong and Kubik (2003) and Bradshaw *et al.* (2016), I calculate the forecast error of an estimate issued by analyst j forecasting for firm i for quarter q of fiscal year t, *Ferror*, as the absolute difference between the actual value and the forecast issued on day d, scaled by one plus the absolute value of the actual:

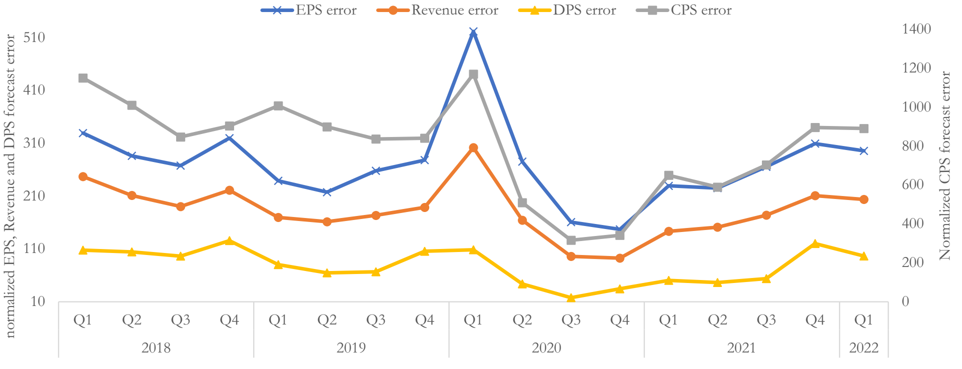
$$Ferror_{i,j,d,q,t} = \frac{\left|Actual_{i,q,t} - Forecast_{i,j,d,q,t}\right|}{1 + \left|Actual_{i,q,t}\right|}. \quad (1)$$

To minimize the impact of outliers, I winsorize forecast errors at 1% and 99%. I use one plus the absolute value of the actual EPS to avoid scaling by zero if a company reports EPS of zero and to avoid very large forecast errors for EPS very close to zero.

Figure 3 presents the mean quarterly forecast error for analyst earnings, revenue, cash flow, and dividend estimates. The forecast errors are comparable across all estimates in 2018 and 2019 (I cannot reject the null hypothesis that the average forecast error is the same in 2018 and 2019). Cash flow forecasts have the largest forecast errors consistent with previous literature (Givoly *et al.*, 2009;

FIGURE 4

UNCERTAINTY-ADJUSTED FORECAST ERRORS FOR ANALYST EARNINGS, REVENUE, CASH FLOW AND DIVIDEND FORECASTS



This figure reports the normalized average quarterly percentage forecast errors for analyst earnings (EPS error), revenue (Revenue error), cash flow (CPS error), and dividend (DPS error) forecasts. Forecast error is calculated as the absolute difference between the actual and forecasted values, scaled by one plus the absolute value of the actual value, which I then scale by the stock return variance estimated from the Fama and French (1993) model over 100 days before the forecast announcement date.

Bilinski, 2014). There is a significant increase in the average forecast error in Q1 of 2020 compared to the average forecast error in Q1 for 2018 and 2019. Forecast errors peak in Q2 of 2020 as firm fundamentals start to fully reflect the impact of the pandemic, including state lockdowns. Forecast errors gradually decline from Q3 of 2020 though remain on average at higher levels compared to the pre-pandemic period.

The evidence in Figure 3 suggests an increase in forecast errors during the pandemic, which is unsurprising given the increase in uncertainty during the pandemic. However, standard measures of forecast error do not answer the question of how forecast accuracy changes per unit of uncertainty: if analyst forecast errors increase at a lower rate compared to the increase in underlying firm uncertainty, investors would find analyst forecast incrementally useful (Loh and Stulz, 2018). Figure 4 repeats the analysis when we scale forecast errors calculated in equation (1) by firm-specific return volatility calculated as the variance of residuals from the Fama and French (1993) model estimated over 100 days before analyst forecast announcement, an approach similar to Loh and Stulz (2018). There is a significant increase in forecast errors per unit of uncertainty in Q1 of 2020, but forecast errors for the remainder of 2020 are either comparable to corresponding pre-pandemic quarters or lower. Forecast errors converge to pre-pandemic levels towards the end of the sample period. Figure 4 suggests that after the initial 'pandemic shock' in Q1 of 2020, analysts were able to apply their skill to produce comparatively more accurate forecasts per unit of uncertainty in the later part of 2020 and early quarters of 2021 compared to the pre-pandemic period.

Institutional Attention and Price Reactions to Analyst Forecast Revisions

The next test looks at institutional attention and price reactions to analyst forecast revisions to assess their usefulness. I calculate the forecast revision, $\Delta Forecast$, as the difference between the analyst's current and previous forecasts issued for the same fiscal quarter q of year t for firm i scaled by the absolute value of the previous forecast,

$$\Delta Forecast_{i,j,d+1,q,t} = \frac{Forecast_{i,j,d+1,q,t} - Forecast_{i,j,d,q,t}}{\left|Forecast_{i,j,d,q,t}\right|}. \tag{2}$$

Using percentage revisions makes forecasts expressed on a per-share basis, for example, EPS estimates, more comparable with forecasts on a non-per-share basis, such as revenue. I winsorize revisions at 1% and 99%.

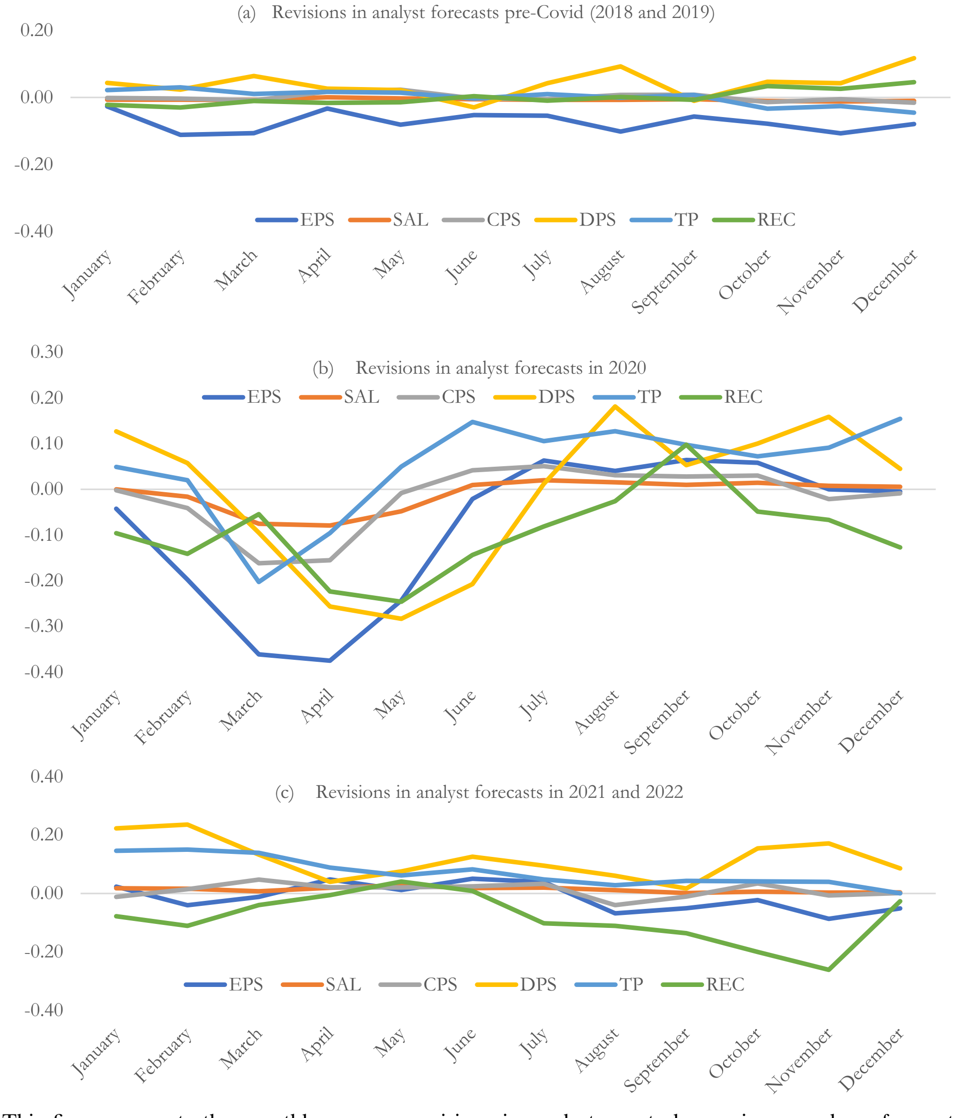
Figure 5 reports the monthly average revisions for the pre-pandemic years, in 2020, and from 2021 to Q1 of 2022. Figure 5a shows similar magnitudes of revisions across months before the pandemic. EPS revisions tend to be negative, which reflects that analysts tend to start at a high forecast level and firms walk-down forecasts to beatable levels (Richardson *et al.*, 2004; Graham *et al.*, 2005). The picture at the start of the pandemic in 2020 is markedly different. Figure 5b shows that analysts revise all forecasts downwards starting in March and up until June 2020 and revisions become smaller in magnitude towards the end of 2020. Figure 5c shows that in 2021 and Q1 of 2022, revisions tend to be more positive and relatively higher in magnitude compared to pre-pandemic years. These results are consistent with analysts significantly updating their forecasts after the start of the pandemic, particularly in the early months of 2020.

Next, I examine if analyst forecast revisions are associated with significant institutional attention as investors first need to become aware of information before they can trade on it. For this test, I use the Bloomberg's News Heat Average Readership Score, which captures firm-specific search activity on Bloomberg terminals. Ben-Rephael *et al.* (2017) highlight that Bloomberg aggregates users' news search and reading of news to create an investor attention score. The attention score, *Attention*, is calculated over a 32-hour period and is assigned a score ranging from zero to four by comparing readership to the previous 30 days. A score of zero indicates readership is less than 80% of the previous 30 days activity, scores one, two, three, and four represent 80%, 90%, 94%, and greater than 96% of the previous readership activity, respectively.[14] I measure attention on the analyst forecast revision day. If the Bloomberg readership score is missing, I assign it a value of zero. To distinguish cases with missing data for a firm on day d from cases where readership is low, I create an

[14] The thresholds are set by Bloomberg.

FIGURE 5

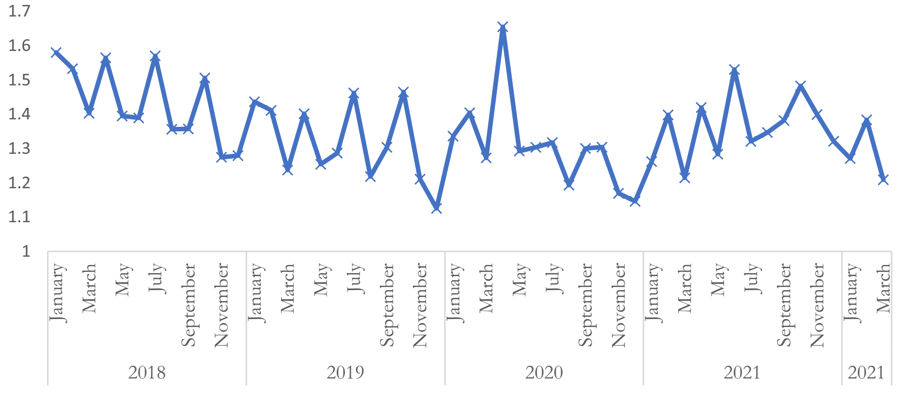
MONTHLY REVISIONS IN ANALYST EARNINGS, REVENUE, CASH FLOW AND DIVIDEND FORECASTS, STOCK RECOMMENDATIONS, AND TARGET PRICES



This figure presents the monthly average revisions in analyst quarterly earnings-per-share forecasts (EPS), revenue forecasts (SAL), cash flow-per-share forecasts (CPS), dividend-per-share forecasts (DPS), target prices (TP), and stock recommendations (REC). I calculate a revision as the difference between the analyst's current and previous forecasts issued for the same fiscal quarter and the same firm scaled by the absolute value of the previous forecast.

FIGURE 6

MONTHLY BLOOMBERG SEARCHES



This figure reports the average monthly Bloomberg readership score.

indicator variable *Missing news dummy* that takes a value of one if the Bloomberg readership score is missing and zero otherwise.

Figure 6 presents the monthly average value of Bloomberg searches around analyst forecast announcements for the sample firms over the pre-pandemic and pandemic months. There is a significant increase in Bloomberg searches at the onset of the pandemic, in April 2020, consistent with investor information searches at the time.

I then regress institutional attention on the forecast issuance day d on absolute forecast revisions using the following model:

$$\begin{aligned} Attention_d = {} & \alpha_0 + \alpha_1|\Delta EPS_d| + \alpha_2|\Delta SAL_d| + \alpha_3|\Delta CPS_d| + \alpha_4|\Delta DPS_d| + \alpha_5|\Delta REC_d| \\ & + \alpha_6|\Delta TP_d| + \alpha_7|\Delta EPS_d| \times Covid + \alpha_8|\Delta SAL_d| \times Covid + \alpha_9|\Delta CPS_d| \\ & \times Covid + \alpha_{10}|\Delta DPS_d| \times Covid + \alpha_{11}|\Delta REC_d| \times Covid + \alpha_{12}|\Delta TP_d| \\ & \times Covid + Missing\ news\ dummy + Firm/Year/Quarter\ effects + \xi. \end{aligned} \tag{3}$$

The regression is estimated using all quarterly forecasts issued by analysts for a firm quarter-year. I omit analyst and firm subscripts in equation (3) for brevity. ΔEPS is the EPS forecast revision, ΔSAL is the revenue forecast revision, ΔCPS is the cash flow forecast revision, ΔDPS is the dividend forecast revision, ΔREC is the stock recommendation revision, and ΔTP is the target price revision. I use absolute values of revisions as I expect analyst revisions to spur investor attention independently of whether revisions are positive or negative. To capture incremental price effects during the pandemic, I interact the revisions with an indicator variable, *Covid*, that takes a value of one from 2020 to Q1 2022 and zero otherwise.[15] Similar to earlier research,

15 As I control for year effects, I do not include the *Covid* variable in the regression. The results are the same when I define COVID as starting from March 2020.

for example, Keung (2010), I assume a zero revision for a forecast not revised jointly with the earnings estimate on day d. The regression controls for firm, calendar year, and quarter fixed effects and ξ is the error term. To avoid confounding effects, I exclude a three-day window centered on the quarterly earnings announcements. Zhang (2008) and Altinkilic and Hansen (2009) highlight that analysts frequently revise their forecasts shortly after quarterly earnings announcements.

The standard measure of forecast informativeness is the price reaction. To test if investors react more strongly to revisions in analyst forecasts during the pandemic, I follow Jung *et al.* (2018) and calculate a three-day absolute cumulative abnormal return, *ACAR*, centered on the forecast revision date, which I then use as a dependent variable in equation (3).[16] I calculate abnormal returns for *ACAR* using the Fama and French (1993) model as the normal return benchmark using daily data over 100 trading days before the forecast announcement. Robustness tests show that the conclusion is unchanged when I use the Carhart (1997) model, the market-adjusted return, and the market model to calculate the normal return benchmark.

An important benefit of including revisions in target prices with revisions in fundamentals in the price reaction regression is that the former control for cross-sectional differences in the discount rate, which can be associated with the magnitude of price reactions (Ali *et al.*, 2009). Specifically, controlling for changes in cash flow expectations, a target price revision reflects changes in the analyst estimate of the expected return, thus the analysis captures both the numerator and denominator effect of changes in analyst expectation of firm value.

Descriptive statistics Table 2 reports descriptive statistics for equation (3). The average readership across the sample years, *Attention*, is 1.184, which reflects that on most analyst forecast announcement days, readership is higher than 80% of readership measured over the prior 30 days. The mean absolute price reaction to analyst forecast revisions is 4.7% in 2018 and 2019, and 5.0% during the COVID-19 pandemic. These magnitudes are comparable to Loh and Stulz (2011) and Altinkilic and Hansen (2009).[17] Compared to pre-pandemic years, there is on average higher magnitude revisions in analyst forecasts during the pandemic, for example, EPS forecast revisions are 45% and revenue forecasts are 69% higher during the pandemic compared to the pre-pandemic period. This result is consistent with the evidence in Figure 3.

Bloomberg searches regression results Table 3 reports results for equation (3). For the baseline model, there are on average significantly higher institutional information searches about a firm on analyst forecast announcement days during the pandemic, consistent with analyst forecasts attracting significant investor

[16] For the price reaction regression, I omit the *Missing news dummy* from the set of controls.

[17] Altinkilic and Hansen (2009, p. 18) report that '[S]tudies show that stock prices fall over 4% at downgrades and rise over 3% at upgrades'.

TABLE 2

DESCRIPTIVE STATISTICS FOR PRICE REACTION REGRESSION VARIABLES

	2018			2019			2020			2021			Q1 2022			Average 2018–Q1 2022
	Mean	STD	p	Mean	STD	p	Mean	STD	p	Mean	STD	p	Mean	STD	p	
Attention	1.226	1.539	0.000	1.126	1.518	0.000	1.178	1.528	0.000	1.205	1.496	0.000	1.211	1.503	0.000	1.184
ACAR	0.047	0.052	0.000	0.048	0.054	0.000	0.057	0.058	0.000	0.045	0.049	0.000	0.050	0.053	0.000	0.049
$\|\Delta EPS\|$	0.174	0.442	0.000	0.187	0.482	0.000	0.326	0.667	0.000	0.213	0.511	0.000	0.243	0.557	0.000	0.228
$\|\Delta SAL\|$	0.020	0.052	0.000	0.021	0.053	0.000	0.044	0.088	0.000	0.029	0.065	0.000	0.031	0.063	0.000	0.029
$\|\Delta CPS\|$	0.022	0.148	0.000	0.021	0.143	0.000	0.032	0.202	0.000	0.022	0.161	0.000	0.026	0.175	0.000	0.025
$\|\Delta DPS\|$	0.001	0.038	0.000	0.001	0.028	0.000	0.002	0.046	0.000	0.002	0.043	0.000	0.002	0.054	0.000	0.002
$\|\Delta REC\|$	0.011	0.105	0.000	0.012	0.119	0.000	0.013	0.111	0.000	0.009	0.091	0.000	0.007	0.087	0.000	0.010
$\|\Delta TP\|$	0.062	0.099	0.000	0.064	0.103	0.000	0.100	0.144	0.000	0.080	0.127	0.000	0.064	0.108	0.000	0.074

This table reports descriptive statistics for the investor attention and price reaction regression variables in equation (3) split by year. *Attention* is the measure of Bloomberg news readership about a firm on the forecast announcement day. *ACAR* is the absolute cumulative abnormal return estimated using the Fama and French (1993) model as the expected return benchmark. ΔEPS is the EPS forecast revision, ΔSAL is the revenue forecast revision, ΔCPS is the cash flow forecast revision, ΔDPS is the dividend forecast revision, ΔREC is the stock recommendation revision, and ΔTP is the target price revision.

TABLE 3

INVESTOR ATTENTION TO ANALYST FORECAST REVISIONS

	Baseline				Firm fixed effects			
	Estimate	*p*	Estimate	*p*	Estimate	*p*	Estimate	*p*
$\|\Delta EPS\|*Covid$	0.028	0.000	0.029	0.000	0.008	0.000	0.008	0.000
$\|\Delta SAL\|*Covid$	0.020	0.000	0.023	0.000	0.054	0.000	0.055	0.000
$\|\Delta CPS\|*Covid$	0.003	0.005	0.004	0.008	0.003	0.000	0.003	0.000
$\|\Delta DPS\|*Covid$	0.003	0.173	0.003	0.170	0.000	0.812	0.000	0.823
$\|\Delta REC\|*Covid$	0.001	0.444	0.001	0.331	0.001	0.459	0.001	0.518
$\|\Delta TP\|*Covid$	0.015	0.000	0.021	0.000	0.100	0.000	0.099	0.000
$\|\Delta EPS\|$	–0.042	0.000	–0.040	0.000	–0.008	0.000	–0.008	0.000
$\|\Delta SAL\|$	–0.018	0.000	–0.020	0.000	0.000	0.548	0.000	0.490
$\|\Delta CPS\|$	0.000	0.895	0.000	0.784	0.002	0.011	0.002	0.016
$\|\Delta DPS\|$	–0.001	0.500	–0.001	0.721	0.002	0.029	0.002	0.030
$\|\Delta REC\|$	–0.001	0.408	0.000	0.705	0.002	0.022	0.002	0.015
$\|\Delta TP\|$	–0.020	0.000	–0.019	0.000	0.004	0.000	0.004	0.000
Missing news dummy	–1.550	0.000	–1.435	0.000	–1.616	0.000	–1.607	0.000
Past Attention			0.106	0.000			0.026	0.000
Year effects	Yes		Yes		Yes		Yes	
Quarter effect	Yes		Yes		Yes		Yes	
Firm effects	No		No		Yes		Yes	
N	644,630		644,630		644,630		644,630	
R^2	64.12%		64.24%		70.84%		70.88%	

This table reports regression results for equation (3) where the dependent variable is a measure of Bloomberg news searches and readership at analyst forecast announcement, *Attention*. *Covid* is an indicator variable equal to one for years 2020 to 2022 and zero otherwise. *Past Attention* measures Bloomberg news searches and readership 15 days before the analyst forecast announcement. Intercepts are omitted for brevity. Standard errors are clustered at the firm and year level.

attention to the firm during that time. Including firm fixed effects in equation (3) produces similar conclusions.

Increased investor attention on a stock can prompt both stronger analyst forecast revisions and a higher reaction to these revisions. To control for the potential *reverse* effect of investor attention before the analyst forecast issuances on analyst revisions and investor Bloomberg searches, I include in equation (3) a measure of past investor attention, which I measure by Bloomberg searches 15 days before the analyst forecast announcement, excluding the announcement day, *Past Attention*. If the evidence in Table 3 is driven by selective attention to some stocks during the pandemic, investor attention preceding forecast issuance should largely explain incrementally significant reactions to analyst forecast revisions. Controlling for past investor attention leaves the conclusions unchanged both for the baseline model and the model with firm fixed effects. Thus, the conclusions are unlikely to be driven by reverse causality.

Price reaction regression results Table 4 reports price reaction regression results for equation (3); for brevity, I report results with firm fixed effects. The baseline

TABLE 4

PRICE REACTION REGRESSION RESULT

	Baseline		Revisions per unit of uncertainty		Analyst fixed effects		Market-model adjusted CAR		Alternative measure of revisions		Firm guidance	
	Estimate	p	Estimate	p	Estimate	p	Estimate	p	Estimate	p	Estimate	p
$\lvert\Delta EPS\rvert * Covid$	0.001	0.000	0.014	0.000	0.002	0.000	0.002	0.000	0.001	0.000	0.003	0.000
$\lvert\Delta SAL\rvert * Covid$	–0.025	0.000	0.016	0.000	–0.011	0.000	–0.029	0.000	-0.025	0.000	–0.012	0.000
$\lvert\Delta CPS\rvert * Covid$	0.002	0.002	0.010	0.000	0.003	0.000	0.003	0.002	0.002	0.002	0.003	0.000
$\lvert\Delta DPS\rvert * Covid$	0.007	0.026	0.006	0.098	0.008	0.006	0.007	0.081	0.007	0.026	0.007	0.007
$\lvert\Delta REC\rvert * Covid$	0.002	0.184	0.004	0.022	0.005	0.000	0.002	0.236	0.002	0.184	0.004	0.000
$\lvert\Delta TP\rvert * Covid$	–0.021	0.000	–0.001	0.715	–0.030	0.000	–0.026	0.000	–0.021	0.000	–0.027	0.000
$\lvert\Delta EPS\rvert$	0.002	0.000	–0.001	0.048	0.000	0.058	0.002	0.000	0.002	0.000	0.000	0.197
$\lvert\Delta SAL\rvert$	0.046	0.000	0.026	0.000	0.028	0.000	0.055	0.000	0.046	0.000	0.031	0.000
$\lvert\Delta CPS\rvert$	0.002	0.005	0.001	0.621	0.002	0.009	0.001	0.222	0.002	0.005	0.001	0.273
$\lvert\Delta DPS\rvert$	0.002	0.393	0.000	0.869	0.002	0.290	0.002	0.491	0.002	0.393	0.002	0.291
$\lvert\Delta REC\rvert$	0.006	0.000	0.002	0.064	0.006	0.000	0.011	0.000	0.006	0.000	0.006	0.000
$\lvert\Delta TP\rvert$	0.071	0.000	0.101	0.000	0.084	0.000	0.109	0.000	0.071	0.000	0.080	0.000
Ret vol			3.496	0.000								
Guidance dummy											–0.010	0.000
Year effects	Yes		Yes		Yes		Yes		Yes		Yes	
Quarter effect	Yes		Yes		Yes		Yes		Yes		Yes	
Firm effects	Yes		Yes		Yes		Yes		Yes		Yes	
Analyst effects	No		No		Yes		No		No		No	
N	644,630		644,630		644,630		644,630		644,630		644,630	
R^2	25.38%		24.28%		32.29%		21.33%		25.38%		25.30%	

The ‘Baseline’ column reports regression results for equation (3) where the dependent variable is the price reaction to analyst forecast revisions. *Covid* is an indicator variable equal to one for years 2020 to Q1 of 2022 and zero otherwise. Intercepts are omitted for brevity. Standard errors are clustered at the firm and year level. The ‘Revisions per unit of uncertainty’ column reports results where I normalize forecast revisions by the volatility of residuals from the Fama and French (1993) model estimated over the previous 100 days. The ‘Analyst fixed effects’ column reports results for equation (3) augmented with analyst fixed effects. The ‘Market-model adjusted CAR’ column reports equation (3) results where the dependent variable is the three-day absolute CAR centered on the analyst forecast announcement date and the normal return benchmark is the market model. The ‘Alternative measure of revisions’ column reports price reaction results where I measure forecast revisions for EPS, cash flows, and dividends by scaling by 1+ the previous forecast. The ‘Firm guidance’ column reports results where I include an indicator variable for whether a firm issued guidance in a three-day window around the analyst forecast issuance.

regression results show incremental price reactions to revisions in analyst EPS forecasts, cash flow, and dividend forecasts. The economic magnitudes of incremental reactions during the pandemic are significant, for example, price reactions to analyst EPS forecast revisions are 83% stronger during the pandemic compared to the pre-pandemic period.[18] Price reactions to revisions in revenue forecasts, target price, and stock recommendations are either zero or negative. These results suggest that investors attach more weight to cash flow signals than discount rate information during the pandemic.

Because uncertainty has increased significantly during the pandemic, I also calculate uncertainty-adjusted revisions in analyst forecasts. Specifically, I follow Loh and Stulz (2018) and calculate uncertainty-adjusted revisions by normalizing revisions in analyst forecasts by firm-specific stock return volatility estimated from the Fama and French (1993) model over 100 days before the forecast announcement. This approach aligns with the normalized forecast errors in Figure 4. Using the normalized revisions confirms incrementally higher price reactions to analyst forecast revisions during the pandemic but for analyst target prices. Normalized revisions in revenue forecasts and in stock recommendations also show a significant association with price reaction, which suggests that using standard measures of revisions during high uncertainty periods may add noise to the analysis, obscuring the relation between price reactions and revisions in analyst forecasts.

Price reaction regressions robustness tests I subject Table 4's results to several robustness tests. First, the evidence in Table 4 could be driven by investor reaction to revisions issued by a select group of high-quality analysts. Though Figure 1 does not suggest changes in analyst firm coverage during the pandemic compared to the pre-pandemic period, to build confidence in the results, I re-estimate equation (3) after including analyst fixed effects. The 'Analyst fixed effects' column in Table 4 suggests that the conclusions are unchanged when controlling for time-invariant analyst characteristics.

Second, the 'Market-model adjusted CAR' column confirms that the results are unchanged when I use the market-adjusted returns to calculate abnormal return for the *ACAR*. This evidence suggests that the results in Table 4 are not influenced by a potential correlation between higher return volatility during the pandemic that impacts the Fama and French (1993) model estimates for the normal return benchmark. In untabulated results, the conclusions are unchanged when I use the market model or the Carhart (1997) model to calculate abnormal returns.

Third, there is a concern that percentage revisions would be inflated for forecasts close to zero. Though I winsorize all revisions, I test the sensitivity of the results to outliers in two ways. First, I re-calculate forecast revisions for EPS, cash flows, and dividends by scaling by 1+ the previous forecast. The 'Alternative measure of revisions' column documents that using these revisions in the regression model

[18] I calculate this as the sum of coefficients on $|\Delta EPS \times Covid$ and $|\Delta EPS|$ dividend by the latter.

leaves the conclusions unchanged. Second, in untabulated results, I remove the top and bottom 5% of observations based on each forecast revision. The conclusions for the trimmed sample are similar to those of the main findings.

Fourth, the sample excludes a three-day window centered on quarterly earnings announcements to avoid the confounding effects of mandatory earnings disclosure. However, it is possible that analyst forecast revisions during the COVID-19 pandemic cluster around firm voluntary disclosure and it is the latter that explains stronger price reactions. To address this concern, I augment equation (3) with an indicator for whether a firm issued guidance during the three-day analyst forecast announcement window. I include both range and point guidance and include guidance for any financial item a firm discloses. The 'Firm guidance' column documents that the conclusions remain unchanged when controlling for a firm's voluntary disclosure.

The main analysis uses absolute price reactions. Table 5 repeats equation (3) for signed measures of price reactions and signed uncertainty-adjusted forecast revisions. The results are consistent with the main findings of incrementally stronger reactions to revisions in analyst forecasts during the pandemic. In untabulated results, I re-estimated equation (3) with control variables that include the book-to-market ratio to capture a firm's growth opportunities, the price-to-sales ratio as a measure of a relative valuation of a firm,[19] the debt-to-assets ratio to capture financial leverage, a firm's return on assets to capture profitability, R&D-to-sales to capture innovation, and advertising-to-sales to capture product visibility to investors, in addition to firm fixed effects. Including these controls reduces the sample size, but the conclusions remain unchanged.

Cross-sectional Tests: Periods of Heightened Information Demand

The evidence in Table 4 suggests that analyst forecasts convey incrementally valuable signals to investors during the pandemic. To sharpen this analysis, I next examine *when* during the pandemic investors have found analyst research particularly valuable. Specifically, I propose that analyst signals are more useful in periods of increased demand for information, which I capture threefold. First, I use average Bloomberg news searches for a stock, measured one month before the analyst forecast issuance, as a measure of investor information demand. Table 6 reports abbreviated equation (3) results augmented with the interaction terms between analyst forecast revisions during the pandemic and the Bloomberg search measure. There are incrementally higher price reactions to analyst forecast revisions during the COVID-19 pandemic in periods of higher Bloomberg search activity.

The second approach to capture investor information search activity follows Da *et al.* (2011) and uses the Google aggregate search frequency for information about COVID-19 and its impact on the stock market. I focus on Google, which accounts for close to 90% of internet searches in the US.[20] Specifically, I create a

[19] The price-to-sales ratio is more useful in valuation for loss-making firms than the price-to-earnings ratio (Damodaran, 2013).

[20] See https://gs.statcounter.com/search-engine-market-share/all/united-states-of-america

TABLE 5

SIGNED REVISIONS

	Estimate	p
Δ*EPS*Covid*	0.005	0.000
Δ*SAL*Covid*	0.042	0.000
Δ*CPS*Covid*	–0.001	0.840
Δ*DPS*Covid*	–0.005	0.380
Δ*REC*Covid*	0.006	0.038
Δ*TP*Covid*	0.032	0.000
Δ*EPS*	–0.010	0.000
Δ*SAL*	–0.036	0.000
Δ*CPS*	0.001	0.395
Δ*DPS*	–0.001	0.873
Δ*REC*	–0.012	0.000
Δ*TP*	0.001	0.839
Ret vol	2.940	0.000
Year effects	Yes	
Quarter effect	Yes	
Firm effects	Yes	
N	644,630	
R^2	4.71%	

This table reports price reaction regression results where I use signed CAR as the dependent variable and signed forecast revisions normalized by the volatility of residuals from the Fama and French (1993) model estimated over the previous 100 days.

variable *Google*, which is the sum of weekly Google searches for the terms 'COVID19', 'COVID', 'Coronavirus', 'SP500', and 'stock market' over the period January 2020 to March 2022. Each weekly Google search term is returned scaled by the average search volume over the search period. Figure 7 presents the time-series distribution of the *Google* measure and it shows a clear spike in search activity at the start of the pandemic, March and April 2020, and a later levelling of internet searches over the reminder of the period. I then interact *Google* with revisions in analyst forecasts over the pandemic period.[21] The results in Table 6 suggest that investors find analyst forecasts particularly useful during COVID-19 when their information demand, as captured by their online search activity, is high.

The third test focuses on periods with scarce availability of firm-specific information. I expect that investors' demand for analyst information, and attention to analyst reports, will be higher in periods of lower availability of firm voluntary disclosure which I capture by a firm's guidance. Specifically, I create an indicator measure for periods with below-median availability of guidance compared to the sample median, which I then use to capture investor demand for information. The

[21] I do not interact the Google measure with revisions during the pre-pandemic period as there are no searches for COVID-19-related terms during that period.

TABLE 6

PRICE REACTIONS CONDITIONAL ON INTENSITY OF INVESTOR INFORMATION SEARCHES

	X = Bloomberg news searches		X = Google news searches		X = below long-term guidance frequency	
	Estimate	p	Estimate	p	Estimate	p
$\|\Delta EPS\|*Covid*X$	0.001	0.000	0.074	0.000	0.041	0.000
$\|\Delta SAL\|*Covid*X$	0.154	0.024	1.238	0.000	0.016	0.000
$\|\Delta CPS\|*Covid*X$	–0.022	0.002	–0.063	0.022	0.011	0.001
$\|\Delta DPS\|*Covid*X$	0.000	0.837	0.000	0.020	–0.008	0.671
$\|\Delta REC\|*Covid*X$	0.236	0.006	–7.266	0.010	0.005	0.002
$\|\Delta TP\|*Covid*X$	2.110	0.000	9.049	0.000	0.046	0.000
X	0.000	0.000	0.000	0.000	0.009	0.000
Other interaction terms	Yes		Yes		Yes	
Year effects	Yes		Yes		Yes	
Quarter effect	Yes		Yes		Yes	
Firm effects	Yes		Yes		Yes	
N	644,630		644,630		644,630	
R^2	21.59%		22.53%		25.99%	

This table reports abbreviated price reaction regression results where I interact all variables with either (i) *Google*, which is the sum of weekly Google searches for the terms 'COVID-19', 'COVID', 'Coronavirus', 'SP500', and 'stock market', or (ii) a measure of institutional ownership in a stock.

last columns of Table 6 confirm that price reactions to analyst forecasts are higher when guidance is scarce.[22]

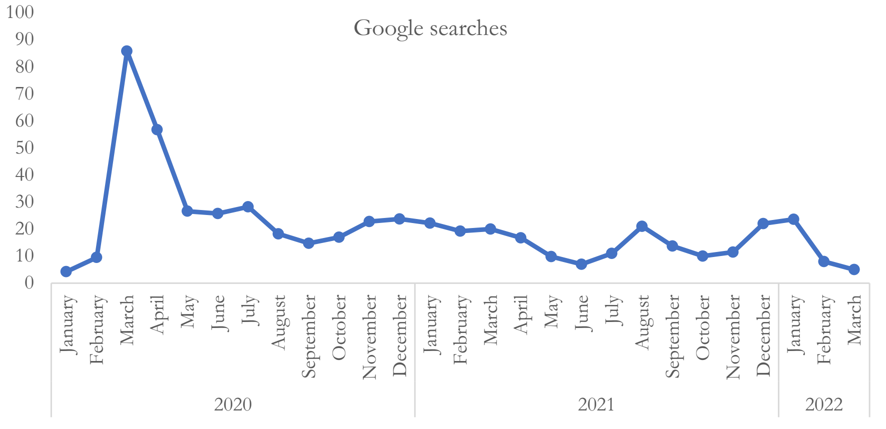
Analyst Information Discovery vs. Interpretation Roles

Several studies examine the role analysts play in discovering private information compared to their role in interpreting public information (e.g., Ivkovic and Jegadeesh, 2004; Asquith *et al.*, 2005). Francis *et al.* (2002) and Frankel *et al.* (2006) report that both functions are important to investors, and Chen *et al.* (2010) document that the analyst information discovery role dominates in the weeks *before* firms announce earnings results while information interpretation is more important in the weeks *after* earnings announcements. I use this insight to examine the weight investors attach to these two roles during the pandemic. Specifically, I

[22] Aaron *et al.* (2021) argue that firms withdraw guidance during the COVID-19 pandemic because of their 'unwillingness to publicly commit to targets when facing macroeconomic adversity and uncertainty', which points to the important commitment role of firm guidance (see also Fuller and Jensen, 2010; Houston *et al.*, 2010). Analyst forecasts do not play such a role, rather, they provide analysts' best estimate of firms' future earnings and this information can factor into investors' decision-making and trading decisions. Analysts have an incentive to generate trading on their research as they are rewarded through 'soft dollar' commissions paid on trades channelled by investors through analyst brokers. Because analysts have different objectives than managers when issuing their forecasts, higher uncertainty prompted by COVID-19 should entice them to issue more research in response to investor demand as their research has more opportunity to generate stock-trading. The incentive to produce research may be amplified by companies withdrawing their guidance thus increasing information asymmetry and consequently investor demand for analyst research.

FIGURE 7

MONTHLY GOOGLE SEARCHES



This figure reports the average monthly cumulative value of weekly Google searches for the terms 'COVID-19', 'COVID', 'COVID19', 'Coronavirus', 'SP500', and 'stock market'. Each Google weekly search term is scaled by the average search volume over the search period January 2020 to March 2022.

TABLE 7

ANALYST INFORMATION DISCOVERY VS INTERPRETATION ROLE

	Estimate	*p*
*ΔEPS*Pre_EA*Covid*	0.002	0.063
*ΔEPS*Covid*	–0.005	0.000
*ΔEPS*Pre_EA*	–0.007	0.000
ΔEPS	0.016	0.000
Pre_EA	–0.002	0.003
*PRE_EA*Covid*	0.002	0.052
Year effects	Yes	
Quarter effect	Yes	
Firm effects	Yes	
N	238,880	
R^2	8.79%	

This table reports regression results for equation (4) which examines price reactions to analyst quarterly forecast revisions before compared to after quarterly earnings announcements. *Pre_EA* equals one for analyst EPS forecast revisions in a 10-day period before earnings announcements and zero otherwise.

select earnings forecasts issued in a 10-day window before and after quarterly earnings announcements and create a variable *Pre_EA*, which takes a value of one for analyst EPS forecast revisions issued in a 10-day period before quarterly earnings announcements and zero otherwise. I then interact this variable with revisions in analyst earnings forecasts and estimate the following model:

$$ACAR_d = \beta_0 + \beta_1|\Delta EPS_d| \times Pre\_EA + \beta_2|\Delta EPS_d| + \beta_3|\Delta EPS_d| \times Pre\_EA \times Covid + \beta_4|\Delta EPS_d| \times Covid + \beta_5 Pre\_EA + \beta_6 Pre\_EA \times Covid + Firm/Year/Quarter\ effects + u \quad (4)$$

where β_1 and β_3 capture incremental price reactions to analyst earnings forecast revision in the short window before earnings announcements, compared to revisions after earnings announcements, before and during the pandemic respectively.[23] As with equation (3), I exclude EPS forecasts issued in a three-day window around earnings announcements to avoid the confounding effect of information released during earnings announcements. The regression is estimated using all quarterly forecasts issued by analysts for a firm quarter-year. The positive coefficient of Δ*EPS***Pre_EA***Covid* and the negative coefficient of Δ*EPS***Covid* in Table 7 suggest that during the pandemic, investors attach more weight to analyst information discovery than interpretation functions. This result is consistent with higher investor information demand for new information that helps them to assess firm performance during the pandemic.

CONCLUSION

This study examines whether and how the COVID-19 pandemic has affected analyst research production and the analyst information intermediation role in the market. It documents that analysts markedly increased their research activity in the initial months of the pandemic compared to similar months before the COVID-19 outbreak with the research intensity converging to pre-pandemic levels towards the later period. Forecasts issued after the initial 'shock' of the pandemic are associated with similar or higher accuracy per unit of uncertainty compared to the pre-pandemic period, which helps explain why investors react incrementally higher to revisions in these estimates compared to the pre-pandemic years. This effect is magnified in periods of increased information demand as captured by Bloomberg and Google searches, and in periods with lower availability of firm voluntary disclosure. I attribute this result to increased investor demand for information that helps assess firm value induced by the COVID-19 outbreak. Further tests reveal that the analyst private information discovery role is more important to investors during the pandemic compared to the information intermediation role.

The study adds new evidence to the debate on the usefulness of analysts as information intermediaries in capital markets in periods of unexpected market shocks, such as the COVID-19 pandemic. The results are relevant for investors, managers, and regulators. During unexpected market-wide tail events such as the pandemic, investors look to financial analysts to help them assess the outlooks of the stocks they hold.

[23] I focus on earnings forecasts as revisions in other estimates tend to be less frequent in the short window around earnings announcements, which leaves relatively few observations.

Thus, it is important for investors to understand how reliable analyst forecasts are during such events, which will guide how much weight investors put on analyst research in their portfolio allocation decisions. The present study is relevant for managers as the increased investment uncertainty during periods of market shock may prompt sudden stock sell-offs and institutional exits that are associated with significant negative consequences for companies, such as higher cost of capital (Demsetz and Lehn, 1985). Analysts can help mitigate these negative consequences by providing valuable research that can reduce information uncertainty, prompting more stable institutional holdings in a stock. The study results are also important to regulators who are still assessing the consequences of COVID-19 in capital markets and the mechanisms that promote more stability in stock prices and ownership structure.[24] The evidence suggests that analysts can play an important information mediation role in the markets in periods of unexpected and unprecedent market turmoil.

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[24] See IMF special series on COVID-19: https://www.imf.org/-/media/Files/Publications/covid19-special-notes/enspecial-series-on-covid19regulatory-and-supervisory-response-to-deal-with-coronavirus-impact-secu.ashx; and the World Bank's COVID-19 Notes: https://pubdocs.worldbank.org/en/776691586478873523/COVID-19-Outbreak-Capital-Markets.pdf

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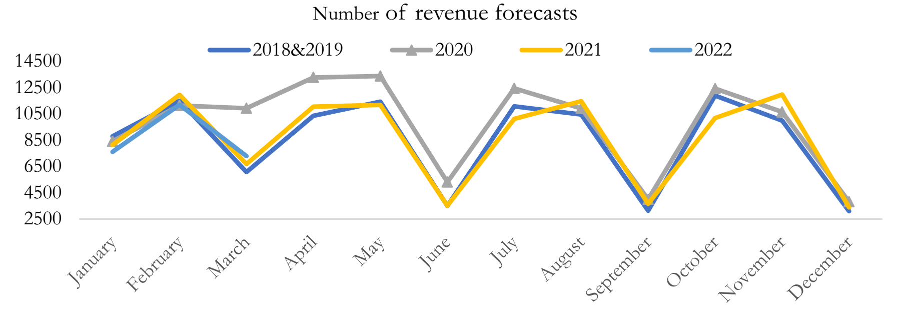
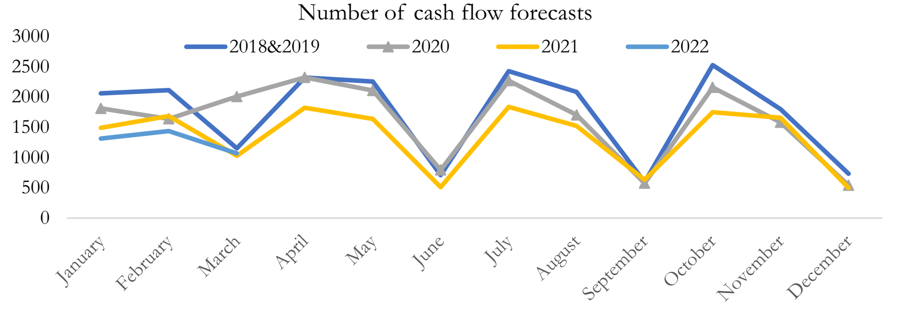
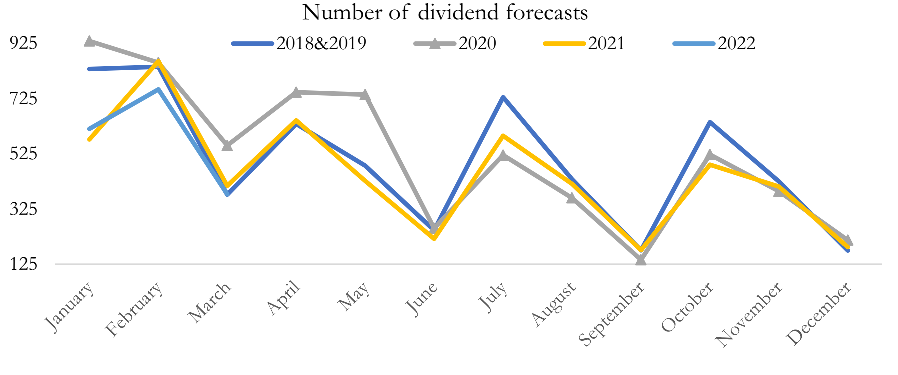
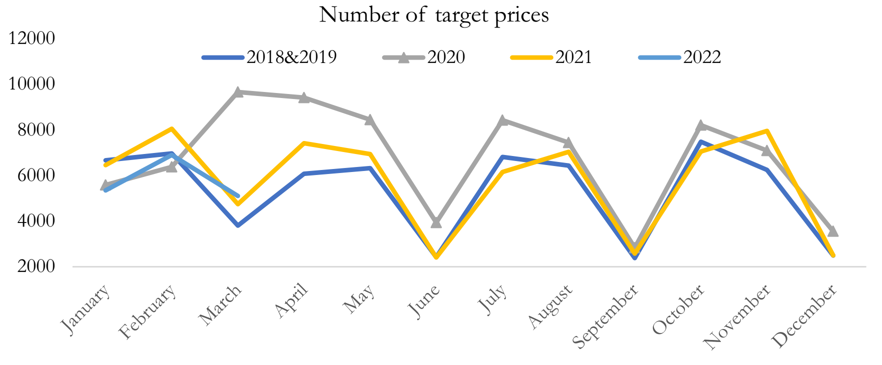
APPENDIX





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2022
January
February
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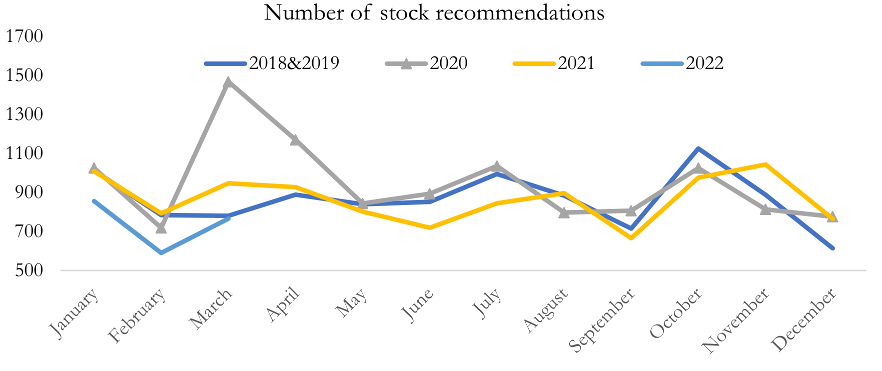
September
October
November
December


Number of stock recommendations
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1500
1300
1100
900
700
500
2018&2019
2020
2021
2022
January
February
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July
August
September
October
November
December