**Analyst research activity during tail-risk events: the case of the COVID-19 pandemic**

**ABSTRACT**

How does the analyst forecasting activity and the usefulness of analyst research change in response to a market-wide tail-risk event? Using the COVID-19 pandemic to capture a tail-risk event, we document that analysts increase their research activity and significantly revise their forecasts during the pandemic compared to the pre-pandemic period. Uncertainty-adjusted forecast accuracy decreases in the first quarter of 2020 but improves in the reminder of 2020. Investor attention and price reactions to forecast revisions are higher during the pandemic and the effect is stronger in periods where investors actively search for information about the pandemic and the stock market as captured by google searches. During the pandemic, investors value analyst price discovery role more than their role in interpreting public information.

**Keywords**: COVID-19; Coronavirus; forecast accuracy; price reactions; information discovery; information intermediation

**JEL**: G01, G14, G32, F14

**1. Introduction**

Tail risk is the chance of an abnormally large loss in firm value due to a rare event as predicted by the probability distribution.[[1]](#footnote-1) The rare chance of a tail-risk event occurring means it is typically studied at the individual firm level with most studies looking at the determinants of stock price crash risk (Chen, Hong and Stein 2001, Jin and Myers 2006, Hutton, Marcus and Tehranian 2009, Kim and Zhang 2014). An important literature stream in this area examined whether changes in analyst coverage predict crash risk events (Kim, Lu and Yu 2019, Xu, Jiang, Chan and Wu 2016), however, no study to date has examined how analyst research activity and research usefulness change in response to a market-wide tail risk event. The surge in uncertainty due to the tail-risk shock increases investor demand for information that helps assess firm fundamentals and value, which in turn should incentivize analysts to exert more effort and increase the frequency and the usefulness of their reports (Grossman and Stiglitz 1980, Bloom 2009, Pastor and Veronesi 2012, Amiram, Landsman, Owens and Stubben 2018). However, the unique nature of the tail-risk event means analysts have no prior experience that would guide their analysis leading to potentially noisy and uninformative research, and to protect their reputation, analysts may reduce their research production (Ertimur, Mayew and Stubben 2011). Further, lockdowns and social distancing restricted analysts’ ability to acquire information through face-to-face meetings with colleagues and managers of firms they followed, which could result in lower quality of outputs. The financial strain on the brokers can also reduce analyst rewards leading to lower analyst motivation for accurate and informative research (Loh and Stulz 2018). Thus, how tail risk events affect analyst research activity and usefulness of analyst reports is an open question.

We tackle our research question empirically by focusing on analyst research activity in response to the COVID-19 pandemic, a unique realization of a market-wide tail-risk shock.[[2]](#footnote-2) Using the COVID-19 setting has important research and econometric benefits. First, it helps us identify how analysts confront unexpected events, thus speaks to analysts’ role as information producers. Previous research provides conflicting evidence on the analyst information discovery role. Early research based on price reactions to analyst forecast announcements suggests 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 past 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). However, Aaron, Kang, Ng and Rusticus (2021, p.1) report that during the pandemic, ‘[A]most half the firms in our sample withdraw their management earnings guidance instead of maintaining or revising it’, reducing the opportunity to piggyback on corporate news. Our research adds novel evidence to the debate on the information production role of analysts in high uncertainty periods with scarce corporate disclosures.[[3]](#footnote-3)

Second, we provide new insights to the literature that examines the value of analyst research in economic downturns, which so far produced mixed results. Loh and Stulz (2018, p.959) report that that in bad times, captured by market recessions, analyst produce more informative research. In contrast, Amiram, Landsman, Owens and Stubben (2018, p.1) argue that when market uncertainty is high, timeliness and forecast accuracy decline. Chen, Zhu and Sang (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, Maaz and Pucker (2015, p.49) report that ‘in recessions sell side analysts are too optimistic about the stocks they recommend to buy’, but Richards, Benjamin and Strawser (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 differences 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 associate with a much different forecasting challenge compared to a tail-risk event. Our focus on the tail-risk event related to the Covid-19 pandemic provides novel evidence on how the informativeness of analyst research changes in response to an unexpected market shock.

Third, the research setting has important econometric benefits. The COVID-19 pandemic is exogenous to firm characteristics thus changes in properties of analyst forecasts cannot be explained by omitted correlated variables. In contrast, the exogeneity of economic downturns studied before cannot be ascertained as these, by definition, associate with deteriorating corporate fundamentals. Thus, the COVID-19 pandemic setting is free of typical endogeneity concerns plaguing accounting research making it a natural laboratory to study the impact a tail-risk event has on analyst behavior and informativeness of their research forecasts. Baker, Bloom, Davis, Kost, Sammon and Viratyosin (2020) document that ‘[N]o previous infectious disease outbreak, including the Spanish Flu, has impacted the stock market as forcefully as the COVID-19 pandemic’ and no other crisis had such a sudden and market-wide impact.

 We collect a sample of 445,561 quarterly earnings-per-share (EPS) forecasts issued between January 2018 and November 2020 for 4,381 unique firms. We classify forecasts issued from January 2020 as pandemic forecasts because (1) Baker et al. (2020) highlight that the ‘the COVID-19 volatility surge began in the fourth week of January’ and (2) the Q1 results for 2020 will be affected by the pandemic forcing analysts to incorporate the effect of COVID-19 into their forecasts.[[4]](#footnote-4) We consider forecasts issued between January 2018 and December 2019 as pre-pandemic forecasts. To understand how the pandemic affected the breadth of analyst research, we also collect quarterly revenue estimates (SAL), cash flow-per-share forecasts (CPS), and dividend-per-share estimates (DPS) issued jointly with the EPS forecasts. We look at revenue forecasts following the evidence in Ertimur, Mayew and Stubben (2011) that 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 allows investors to disaggregate earnings estimates into accrual and cash flow estimates allowing to gauge earnings persistence and the likelihood of financial distress (DeFond and Hung 2003, Givoly, Hayn and Lehavy 2009). Dividend forecasts gauge future payouts and contain incremental information compared to earnings, revenue and cash flow estimates and help investors assess persistence of earnings (Bilinski and Bradshaw 2020). In testing the informativeness of forecast revisions, we also look at analyst target prices and stock recommendations, which reflect an analyst’s investment advice.

 We first examine changes in the supply of analyst forecasts in response to the COVID-19 pandemic. We 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 22% between April and July 2020, reducing towards the end of 2020. Similar patterns are evident for other forecasts. Compared to the same pre-pandemic months, the number of revenue forecasts increases in March by 80%, cash flow forecasts by 59% and dividend estimates by 11% and declines to pre-pandemic levels towards the end of 2020. The number of target prices is 154% and stock recommendations is 88% higher in March 2020 compared to same month before the pandemic. Thus, the analysts’ initial response to the pandemic-induced market uncertainty is to increase provision of information.

 Next, we examine the forecast errors. EPS forecast errors increases by 76.8% for Q1 2020 results compared to same quarter before the pandemic and reduce gradually to a 37.5% higher error in quarter 4. Compared to the pre-pandemic period, revenue forecast error is on average 62.1% higher during the pandemic, cash flow forecast error is up by 14.9%, and divined forecast errors are on average 17.9% higher. Thus, research production during the pandemic associates 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 we calculate uncertainty-adjusted forecast error following Loh and Stulz (2018), we find that forecast errors per unit of uncertainty are either comparable or smaller during the pandemic compared to the pre-pandemic levels, but for Q1 of 2020.

 Next, we 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 (BenRephael, Dan and Israelsen 2017) and (2) price reaction regressions. We focus on institutional attention because BenRephael 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 direct investors’ attention to the firm helps us understand why investors trade on analyst forecasts. We examine institutional attention rather than retail attention more commonly captured by google searches because institutional ownership account for more than 80% of common equity ownership in the US since (Stambaugh, 2014).[[5]](#footnote-5) We then focus on price reactions to examine if analyst revisions reveal valuable information that investors use to guide their investment decisions (Stickel 1995, Womack 1996).

We document two results. First, compared to the pre-pandemic period, we observe significant revisions in all analyst forecasts during the pandemic: the absolute magnitude of analyst revisions are 112% higher for EPS forecasts, 142% for revenue estimates, 64% for cash flow forecasts and 106% for dividend estimates. We also observe 9% stronger recommendation revisions and 57% higher absolute price target revisions. Thus, analysts actively update their forecasts during the pandemic. Second, regression analysis show that institutional attention, as measured by Bloomberg news searches, is higher around analyst forecast announcements during the pandemic compared to pre-pandemic period. Further, we confirm that investors react more strongly during the pandemic to revisions in analyst forecasts and in stock recommendations compared to the pre-pandemic period.[[6]](#footnote-6) These results are consistent with the Bayesian framework (e.g., Pastor and Veronesi 2009) that as the accuracy of analyst signals relative to the uncertainty increases, investors put more weight on these signals. The economic effects are large, for example, price reactions to EPS forecast revisions are 100% higher during pandemic compared to the pre-pandemic period. The conclusions are robust to alternative measures of price reactions, of analyst forecast revisions, and to including firm-fixed effects in the model.

 To shed more light on why investors put more weight on analyst forecasts during the pandemic, we perform two tests. First, we examine the role analyst research plays in resolving uncertainty during periods of increased investor demand for information. We capture information demand by the intensity of google searches for the pandemic and stock market information.[[7]](#footnote-7) We find that price reactions to analyst forecast revisions are incrementally higher during periods of increased google searches. This result is consistent with analysts responding to higher investor information demand.

Second, we examine whether investors value analyst private information discovery role more than their role in interpreting corporate information during the pandemic. Chen, Cheng and Lo (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. We follow Chen et al. (2010) and focus on EPS forecasts in a 10-day window around earnings announcements excluding a three-day window centered on the earnings announcement day to avoid confounding effects. We find that before the pandemic, price reactions are similar in magnitude before and after earnings announcements, a result consistent with Francis, Schipper and Vincent (2002) and Frankel, Kothari and Weber (2006) who document that investors value both analysts information discovery and interpretative functions. However, during the pandemic, investors value more analyst private information discovery role, a result consistent with greater demand for private information discovery.

 This study offers several contributions. First, we contribute to the accounting literature that examines the capital markets consequences of analyst research. This literature examined the accuracy and price impact of analyst forecasts, and the importance of analyst information discovery role compared to the information interpretative function (Dempsey 1989, Shores 1990, Womack 1996, Loh and Stulz 2011, Ivkovic and Jegadeesh, 2004, Chen, Cheng and Lo 2010). We document how the COVID-19 pandemic, a tail-risk event, affected analysts research production, accuracy of their forecasts, and investor assessment of analyst research information content. Further, we report significant value of analyst information intermediation role during periods of high market uncertainty. Our evidence contrasts the view on the declining importance of sell-side analysts in the market stemming from regulatory changes, such as Markets In Financial Instruments Directive II in Europe (Fang, Hope, Huang and Moldovan 2020), declining research budgets, and an increasing shift to passive ownership (Appel, Gormley and Keim 2016).[[8]](#footnote-8)

Second, the study contributes to the literature on the consequences of market shocks, such as tail and crash risk events. The literature on crash risk has focused on its determinants as studying consequences suffers from the inherent endogeneity problem. Habib, Hasan and Jiang (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.’[[9]](#footnote-9) The exceptions are An, Li and Yu (2015), who examine the speed of leverage adjustment following a crash risk, and Wu (2013), who report that CEO turnover increases in the year after crash risk. Our study contributes novel evidence on the consequences of tail-risk event for analyst research production and informativeness of their research.

Third, we add to the growing literature on the impact COVID-19 had 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 largest NYSE, Nasdaq, or Amex stocks during the COVID-19 crisis. Cox, Greenwald and Ludvigson (2020) estimate a dynamic asset pricing model to capture fluctuations in the pricing of stock market risk during the pandemic. Ding, Levine, Lin and Xie (2020) study firm characteristics that predict the magnitude of share price drop in response to 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, Liu, Mai and Zhang (2021) report that firms with a strong corporate culture outperform peers with a weak culture during the pandemic. Cejnek, Randl and Zechner (2020) study the effect COVID-19 had on corporate dividend policy, Anginer, Donmez, Seyhun and Zhang (2020) on insider trades, and Tkachenko and Bataeva (2020) on share repurchases. Fahlenbrach, Rageth and Stulz (2020) study the effect financial flexibility has on the share price reaction to COVID-19 outbreak. Our evidence showcases analyst response to the pandemic.

**2. Data**

We collect analyst individual quarterly EPS forecasts and contemporaneously issued revenue, cash flow and dividend estimates, target prices and stock recommendations from I/B/E/S over the period January 2018 to November 2020. I/B/E/S imposes a four-month gap between when the data is available for academic compared to commercial research, which determines the end of our sample period. We require that the forecasts have the actual value to calculate forecast errors and share price information on CRSP. Our final sample includes 445,561 EPS forecasts issued for 4,381 unique firms by 2,997 unique analysts employed by 253 unique brokers.

 Table 1 presents the annual number of forecasts between 2018 and 2020. The fraction of revenue forecasts issued with EPS estimates is 66.6%, a result consistent with Ertimur et al. (2011) that since 2001, almost all analysts produce revenue estimates. We find that 13.1% 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 a fraction that is higher than 9.3% in Bilinski (2014) over the period 2000-2008. Around 3.9% of EPS estimates are issued jointly with a dividend forecast, an evidence consistent with Bilinski and Bradshaw (2020) that dividend forecasts are rare in the U.S.. Target prices are issued with 42.8% of earnings forecasts, and stock recommendations with around 6.6% of EPS estimates.

[Table 1]

**3. Empirical results**

This section first presents results on the supply of analyst forecasts during the pandemic compared to pre-pandemic years. Then we examine forecast accuracy and finally the usefulness of the forecasts.

*3.1 The 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 EPS, revenue, cash flow and dividend forecasts, target prices and stock recommendations in the pre-pandemic years 2018 and 2019 and during 2020. We identify two main results. First, the number of forecasts is markedly similar in 2018 and 2019, which suggests a routine in analyst research production.[[10]](#footnote-10) Second, there is a visible increase in the number of forecasts in March 2020, the month that observed the most dramatic volatility in market indices during the pandemic. Compared to the same pre-pandemic month, the number of quarterly EPS forecasts increases by 72.4% in March 2020, revenue forecasts by 79.5%, cash flow forecasts by 58.7%, dividend estimates by 11%, target prices by 154.3%, and stock recommendations by 88.2%. After this initial increase, we observe a gradual reduction in the number of forecasts and a convergence to pre-pandemic levels around August 2020, with a slight decline below pre-pandemic numbers in the last sample months. Figure 1 evidence is consistent with analysts promptly responding to the onset of market uncertainty caused by the pandemic shock by increasing their information provision.

[Figure 1]

*3.2 Forecast accuracy*

Next, we examine the accuracy of analyst forecasts. Because the forecasts we use are on a per-share and non-per-share basis, we require measures of forecast error that is scale independent. Following Hong and Kubik (2003) and Bradshaw, Lee and Peterson (2016), we calculate the forecast error at the analyst level *j* 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 1 plus the absolute value of the actual:

$Ferror\_{i,j,d,q,t+1}=\frac{\left|Actual\_{i,q,t+1}-Forecast\_{i,j,d,q,t+1}\right|}{1+|Actual\_{i,q,t+1}|}$. (1)

To minimize the impact of outliers, we winsorize forecast errors at the 1% and 99%.

 Figure 2 presents the mean quarterly forecast error for analyst earnings, revenue, cash flow and dividend estimates.[[11]](#footnote-11) We observe comparable forecast errors across all measures in 2018 and 2019 (we cannot reject the null hypothesis that the average forecast error is the same in 2018 and 2019). We observe a significant increase in the average forecast error in Q1 of 2020 compared to the average forecasts 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. Forecasts errors gradually decline in Q3 and Q4.

[Figure 2]

 Figure 2 evidence suggests an increase in forecast errors, which is unsurprising given the uncertainty increase during to 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 useful (Loh and Stulz 2018). Figure 3 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 Carhart (1997) model estimated over 100 days before analyst forecast announcement, an approach similar to Loh and Stulz (2018). We observe a significant increase in forecast errors per unit of uncertainty in Q1 of 2020, but forecast errors for the reminder of the year are either comparable to corresponding pre-pandemic quarters or lower. Figure 3 evidence 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.

[Figure 3]

*3.3 Institutional attention and price reactions to analyst forecast revisions*

Our next test looks at institutional attention and price reactions to analyst forecast revisions to assess their usefulness. We calculate the forecast revision, $ΔForecast$, as the difference between the analyst current and previous forecast issued for the same fiscal quarter and the same firm scaled by the absolute value of the previous forecast,

$ΔForecast\_{i,j,d+1,q,t+1}=\frac{Forecast\_{i,j,d+1,q,t+1}-Forecast\_{i,j,d,q,t+1}}{\left|Forecast\_{i,j,d,q,t+1}\right|}.$ (2)

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

 Figure 4 reports the monthly average revisions for the pre-pandemic years and for 2020. We observe very 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 level and firms walk-down forecasts to beatable levels (Richardson et al. 2004, Graham, Harvey and Rajgopal 2005). The picture during the pandemic is markedly different: analysts revise downwards all forecasts starting in March up till June 2020 and revisions become smaller in magnitude towards the end of 2020.

[Figure 4]

 Next, we examine if forecast revisions associate with significant institutional attention as investors first need to become aware of information before they would trade on it. For this test, we use the Bloomberg’s News Heat Average Readership Score, which captures firm-specific search activity on Bloomberg terminals. BenRephael 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 0-4 by comparing readership to the previous 30 days. A score of 0 indicates readership is less than 80% of the previous 30 days activity, scores 1, 2, 3, and 4 represent 80%, 90%, 94% and greater than 96% of the previous readership activity, respectively. We measure attention on the analyst forecast revision day. If the Bloomberg readership score is missing, we assign a value of 0. To distinguish cases with missing data from cases where readership is low, we create an indicator variable *Missing news dummy* that takes a value of 1 if the Bloomberg readership score is missing and zero otherwise. We then regress institutional attention measure on absolute forecasts revisions using the following model:

|  |  |
| --- | --- |
| $$Attention\_{d}=α\_{0}+α\_{1}\left|ΔEPS\_{d}\right|+α\_{2}\left|ΔSAL\_{d}\right|+α\_{3}\left|ΔCPS\_{d}\right|+α\_{4}\left|ΔDPS\_{d}\right|+α\_{5}\left|ΔREC\_{d}\right|+α\_{6}\left|ΔTP\_{d}\right|+α\_{7}\left|ΔEPS\_{d}\right|×Covid+α\_{8}\left|ΔSAL\_{d}\right|×Covid+α\_{9}\left|ΔCPS\_{d}\right|×Covid+α\_{10}\left|ΔDPS\_{d}\right|×Covid+α\_{11}\left|ΔREC\_{d}\right|×Covid+α\_{12}\left|ΔTP\_{d}\right|×Covid+Missing news dummy+Firm/Year/Quarter effects+ξ.$$ | (3) |

We omit analyst and firm subscripts in equation (3) for brevity. Δ*EPS* is the EPS forecast revision, Δ*SAL* is the revenue forecast revision, Δ*CPS* the cash flow forecast revision, Δ*DPS* is the dividend forecast revision, Δ*REC* the stock recommendation revisions, and Δ*TP* the target price revision. We use absolute values of revisions as we expect analyst revisions to spur investor attention independently of whether revisions are positive or negative. To make economic magnitudes of coefficients comparable between variables, we standardize all revisions to a mean of zero and unit standard deviation.[[12]](#footnote-12) To capture incremental price effects during the pandemic, we interact the revisions with an indicator variable, *Covid*, that takes a value of one during 2020 and zero otherwise.[[13]](#footnote-13) Similar to earlier research, e.g. Keung (2010), we 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 calendar quarter-fixed effects and $ξ$ is the error term. To avoid confounding effects, we exclude a three-day window centered on the quarterly earnings announcements. Zhang (2008) and Altinkilic and Hansen (2009) highlight that analysts 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, we follow Jung, Naughton, Tahoun and Wang (2018) and calculate a three-day absolute cumulative abnormal return, *ACAR,* centered on the forecast revision date, which we then use as a dependent variable in equation (3).[[14]](#footnote-14) We calculate abnormal returns for *ACAR* using the Carhart (1997) model as the normal return benchmark using daily data over 100 trading days before the forecast announcement. Robustness tests show our conclusion are unchanged when we use the market-adjusted return and the market model to calculate the 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 the cross-sectional differences in the discount rate, that can associate with the magnitude of price reactions (Yeung 2009). Specifically, controlling for changes in cash flow expectations, a target price revision reflects changes in the analyst estimate of the expected return, thus our analysis captures both the numerator and denominator effect of changes in analyst expectation of firm value.

*3.3.1 Regression results*

 Panel A of Table 2 reports descriptive statistics for equation (3). The average readership measure is 1.226, which reflects that on most forecast announcement days, readership is higher than 80% of readership measured over prior 30 days. The mean absolute price reaction to analyst forecast revisions is 5% in 2018 and 5.1% in 2019, but 6% in 2020. These magnitudes are comparable to Loh and Stulz (2011) and Altinkilic and Hansen (2009).[[15]](#footnote-15) Compared to pre-pandemic years, we observe significant revisions in all analyst forecasts during the pandemic ranging between 9% for stock recommendations to 142% for sales revenue, a result consistent with Figure 3.

[Table 2]

 Table 3 reports results for equation (3). We observe significantly higher institutional information searches about a firm on analyst forecast announcement days during the pandemic, consistent with analyst forecasts attracting investor attention to the firm. For the baseline regression, we find that all forecasts illicit significantly higher information searches on Bloomberg during the pandemic. Including firm-fixed effects in equation (3), shows that revisions in revenue and cash flow forecasts associate with a significant incremental investor attention and revisions in target prices with lower attention. These results suggest investors weight more cash flow that discount rate news during the pandemic.

[Table 3]

Table 4 reports price reaction regression results for equation (3). For the model with firm-fixed effects, we find incremental price reactions to revisions in EPS, cash flow, dividend and stock recommendations, and lower price reactions to target price revisions. The economic magnitudes of incremental reactions during the pandemic are significant, for example, price reactions to analyst EPS forecast revisions are 100% stronger during the pandemic compared to the pre-pandemic period.[[16]](#footnote-16) These results are consistent with Figure 3 evidence that forecast errors, per unit of uncertainty, are lower in the later part of 2020 thus convey incrementally useful information to investors. The results are also consistent with Table 3 evidence that investors attach more weight to cash flow signals than discount rate information during the pandemic.

*3.3.2 Robustness tests*

Table 5 reports robustness tests for the price reaction regressions. For brevity, we report the regressions for the model with firm-fixed effects. First, we confirm that our results are unchanged when we use the market-adjust returns to calculate abnormal return for the *ACAR*. This evidence suggests our results in Table 4 are not influenced by a potential correlation between higher return volatility during the pandemic that impacts the Carhart (1997) model estimates for the normal return benchmark and the pandemic period indicator. Second, our conclusions are unchanged when we use the market-model. Third, there is a concern that percentage revisions would be inflated for forecasts close to zero. Though we winsorize all revisions, we test sensitivity of our results to outliers in two ways. First, we re-calculate forecast revisions for EPS, cash flows and dividends by scaling by 1+the previous forecast. Using these revisions in the regression model leaves our conclusions unchanged. Second, we remove top and bottom 5% of observations based on each forecast revisions. The conclusions for the trimmed sample are similar to our main findings. Fourth, we follow Loh and Stulz (2018) and calculate uncertainty-adjusted revisions by normalizing revisions by firm-specific stock return volatility estimated from the Carhart (1997) model over 100 days before forecast announcement. This approach aligns with the normalized forecast errors in Figure 3. Using the normalized revisions confirms incrementally higher price reactions to analyst forecast revisions during the pandemic. Further, normalized revisions in revenue forecasts show a significant association with price reaction, which suggests that using standard measures of revision during high uncertainty periods may add noise to the analysis obscuring the relation between price reactions and revisions in analyst forecasts.

In untabulated results, we re-estimated equation (3) with control variables that include the book-to-market ratio to capture firm’s growth opportunities, the price-to-sales ratio as a measure of the relative valuation of a firm,[[17]](#footnote-17) debt-to-assets ratio to capture financial leverage, 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 our conclusions remain unchanged.

[Table 5]

 Our main analysis uses absolute price reactions. Table 6 repeats equation (3) for signed measures of price reactions and normalized forecast revisions. The results are consistent with our main findings of incrementally stronger reactions to revisions in analyst forecasts during the pandemic.

[Table 6]

*3.4 Cross-sectional tests: Periods of heighted information demand*

The evidence in Table 4 suggests analyst forecasts convey incrementally valuable signals to investors during the pandemic. To sharpen this analysis, we next examine *when* during the pandemic investors found analyst research particularly valuable. First, we propose that analyst signals are more useful in periods of increased information demand. To capture investor information search activity, we follow the approach from Da et al. (2011) and use the Google aggregate search frequency for information about COVID-19 and its impact on the stock market. We focus on Google, which accounts for close to 90% of internet searches in the U.S..[[18]](#footnote-18) Specifically, we create a 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 December 2020. Each weekly google search term is returned scaled by the average search volume over the search period. Figure 5 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 2020, and a later levelling of internet searches over the reminder of 2020. We then interact *Google* with revisions in analyst forecasts over the pandemic period.[[19]](#footnote-19)

[Figure 5]

Table 7 report abbreviated equation (3) results augmented with the interaction terms between analyst forecast revisions during the pandemic and the google search measure. We observe that all interaction terms are positive, which suggests that investors find analyst forecasts particularly useful when their information demand, as captured by their online search activity, is high.

[Table 7]

*3.5 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. Chen et al. (2010) document that analyst information discovery role dominates in the weeks before firms announce their earnings and information interpretation is more important in the weeks after earnings announcements. We use this insight to examine the weight investors attach to these two roles. Specifically, we 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 one for analyst EPS forecast revisions issued in a 10-day period before quarterly earnings announcements and zero otherwise. We then interact this variable with revisions in analyst earnings forecasts and estimate the following model

|  |  |
| --- | --- |
| $$ACAR\_{d}=β\_{0}+β\_{1}\left|ΔEPS\_{d}\right|×Pre\\_EA+β\_{2}\left|ΔEPS\_{d}\right|+β\_{3}\left|ΔEPS\_{d}\right|×Pre\\_EA×Covid+β\_{4}\left|ΔEPS\_{d}\right|×Covid+β\_{5}Pre\\_EA+β\_{6}Pre\\_EA×Covid+Firm/Year/Quarter effects+u$$ | (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.[[20]](#footnote-20) As with equation (3), we exclude EPS forecasts issued in a three-day window around earnings announcements to avoid the confounding effect of earnings announcements.

 Table 8 results confirm the evidence in Francis et al. (2002) and Frankel et al. (2006) that, in the pre-pandemic period, both analyst interpretation and information discovery roles are important to investors. However, 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 assess firm performance during the pandemic.

[Table 8]

**4. Conclusions**

This study examines how a tail-risk event, as captured by the COVID-19 pandemic, affected analyst research production and analyst information intermediation role in the market. We document that analysts increase their research activity in the initial months of the pandemic compared to similar months before the COVID-19 outbreak. Forecasts issued in the later part of 2020 associate with similar or higher accuracy per unit of uncertainty and investors react incrementally higher to revisions in analyst estimates compared to the pre-pandemic years. This effect is magnified in periods of increased information demand as captured by googles searches for coronavirus and stock market information. We attribute this result to increased investor demand for information that helps assess firm value induced by the COVID-19 outbreak. Further tests reveal that analyst private information discovery role is more important to investors during pandemic compared to the information intermediation role. Overall, the study adds important evidence to the debate on the usefulness of analysts as information intermediaries in capital markets.

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**Figure 1.** The monthly number of forecasts

|  |  |
| --- | --- |
|  |  |

The figure reports the monthly number of analyst earnings forecasts, revenue, cash flow, dividend, target price, stock recommendations issued between January 2018 and November 2020.

**Figure 2.** Quarterly forecast error

The figure reports the average quarterly percentage forecast error for analyst earnings, revenue, cash flow and dividend forecasts. Forecast error is calculated as absolute difference between the actual and forecasted values, scaled by 1 plus the absolute value of the actual.

**Figure 3.** Uncertainty-adjusted forecast errors

The figure reports normalized average quarterly percentage forecast error 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 1 plus the absolute value of the actual, which we then scale by the stock return variance estimated from the Carhart (1997) model over 100 days before the forecast announcement date.

**Figure 4.** Monthly average revisions in analyst forecasts

The 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. We calculate a revision as the difference between the analyst current and previous forecasts issued for the same fiscal quarter and the same firm scaled by the absolute value of the previous forecast.

**Figure 5.** Monthly google searches from January to December 2020

The figure reports the average monthly cumulative value of weekly Google searchers 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 December 2020.

TABLE 1

The annual distribution of analyst forecasts

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | 2018 | 2019 | 2020 | Total  |
| Earnings forecasts (EPS) | 157546 | 152965 | 135050 | 445561 |
| Revenue forecasts (SAL) | 102430 | 101212 | 93119 | 296761 |
| % of EPS forecasts | 65.02% | 66.17% | 68.95% | 66.6% |
| Cash flow forecasts (CPS) | 22443 | 19948 | 15787 | 58178 |
| % of EPS forecasts | 14.25% | 13.04% | 11.69% | 13.1% |
| Dividends forecasts (DPS) | 6446 | 6107 | 5021 | 17574 |
| % of EPS forecasts | 4.09% | 3.99% | 3.72% | 3.9% |
| Target prices (TP) | 65380 | 60680 | 64632 | 190692 |
| % of EPS forecasts | 41.50% | 39.67% | 47.86% | 42.8% |
| Stock recommendations (REC) | 10781 | 9489 | 9085 | 29355 |
| % of EPS forecasts | 6.84% | 6.20% | 6.73% | 6.6% |

*Notes:* The table reports the annual number of analyst individual 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.

TABLE 2

Descriptive statistics for price reaction regression variables

|  |  |  |  |
| --- | --- | --- | --- |
|   | 2018 | 2019 | 2020 |
|   | Mean | STD | p | Mean | STD | p | Mean | STD | p |
| Attention | 1.226 | 1.539 | 0.000 | 1.126 | 1.518 | 0.000 | 1.190 | 1.528 | 0.000 |
| ACAR | 0.050 | 0.055 | 0.000 | 0.051 | 0.057 | 0.000 | 0.060 | 0.061 | 0.000 |
| |∆EPS| | 0.169 | 0.445 | 0.000 | 0.185 | 0.491 | 0.000 | 0.375 | 0.732 | 0.000 |
| |∆SAL| | 0.025 | 0.056 | 0.000 | 0.026 | 0.057 | 0.000 | 0.061 | 0.101 | 0.000 |
| |∆CPS| | 0.024 | 0.160 | 0.000 | 0.022 | 0.153 | 0.000 | 0.038 | 0.223 | 0.000 |
| |∆DPS| | 0.002 | 0.033 | 0.000 | 0.001 | 0.027 | 0.000 | 0.003 | 0.049 | 0.000 |
| |∆REC| | 0.011 | 0.107 | 0.000 | 0.012 | 0.121 | 0.000 | 0.013 | 0.115 | 0.000 |
| |∆TP| | 0.064 | 0.097 | 0.000 | 0.064 | 0.101 | 0.000 | 0.101 | 0.141 | 0.000 |

*Notes:* The 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 Carhart (1997) model as the expected return benchmark. Δ*EPS* is the EPS forecast revision, Δ*SAL* is the revenue forecast revision, Δ*CPS* the cash flow forecast revision, Δ*DPS* the dividend forecast revision, Δ*REC* the stock recommendation revision, and Δ*TP* the target price revision.

TABLE 3

Investor attention to analyst forecast revisions

|  |  |  |
| --- | --- | --- |
|  | Baseline | Firm-fixed effects |
|   | Estimate | p | Estimate | p |
| |∆EPS|\*Covid | 0.082 | 0.000 | -0.002 | 0.251 |
| |∆SAL|\*Covid | 0.054 | 0.000 | 0.003 | 0.078 |
| |∆CPS|\*Covid | 0.009 | 0.000 | 0.002 | 0.035 |
| |∆DPS|\*Covid | 0.003 | 0.018 | 0.000 | 0.736 |
| |∆REC|\*Covid | 0.007 | 0.000 | 0.001 | 0.252 |
| |∆TP|\*Covid | 0.084 | 0.000 | -0.008 | 0.000 |
| |∆EPS| | -0.047 | 0.000 | -0.002 | 0.281 |
| |∆SAL| | -0.047 | 0.000 | -0.010 | 0.000 |
| |∆CPS| | -0.002 | 0.135 | 0.007 | 0.000 |
| |∆DPS| | -0.001 | 0.415 | 0.001 | 0.251 |
| |∆REC| | -0.005 | 0.000 | 0.001 | 0.578 |
| |∆TP| | -0.051 | 0.000 | 0.008 | 0.000 |
| Missing news dummy | -1.470 | 0.000 | -1.457 | 0.000 |
| Year effects | Yes |  | Yes |  |
| Quarter effect | Yes |  | Yes |  |
| Firm effects | No |  | Yes |  |
| N | 445561 |  | 445561 |  |
| R2 | 59.57% |   | 69.94% |   |

*Notes*: The table reports regression results for equation (3) where the dependent variable is a measure of Bloomberg news searchers and readership at analyst forecast announcement, *Attention*. *Covid* is an indicator variable equal to one for year 2020 and zero otherwise. Intercepts omitted for brevity. All variables are standardized to a mean of zero and unit standard deviation. Standard errors clustered at the firm and year level.

TABLE 4

Price reaction regression result

|  |  |  |
| --- | --- | --- |
|  | Baseline | Firm-fixed effects |
|   | Estimate | p | Estimate | p |
| |∆EPS|\*Covid | -0.061 | 0.000 | 0.011 | 0.000 |
| |∆SAL|\*Covid | -0.005 | 0.446 | 0.000 | 0.913 |
| |∆CPS|\*Covid | 0.021 | 0.000 | 0.014 | 0.000 |
| |∆DPS|\*Covid | 0.010 | 0.000 | 0.006 | 0.001 |
| |∆REC|\*Covid | 0.004 | 0.262 | 0.006 | 0.000 |
| |∆TP|\*Covid | -0.086 | 0.000 | -0.026 | 0.000 |
| |∆EPS| | 0.073 | 0.000 | 0.011 | 0.000 |
| |∆SAL| | 0.068 | 0.000 | 0.011 | 0.000 |
| |∆CPS| | -0.011 | 0.000 | -0.001 | 0.633 |
| |∆DPS| | -0.012 | 0.000 | 0.001 | 0.515 |
| |∆REC| | 0.011 | 0.001 | 0.008 | 0.000 |
| |∆TP| | 0.297 | 0.000 | 0.168 | 0.000 |
| Year effects | Yes |  | Yes |  |
| Quarter effect | Yes |  | Yes |  |
| Firm effects | No |  | Yes |  |
| N | 445561 |  | 445561 |  |
| R2 | 7.89% |   | 27.93% |   |

 *Notes:* The table reports regression results for equation (3) where the dependent variable is the price reaction to analyst quarterly forecast revisions. *Covid* is an indicator variable equal to one for year 2020 and zero otherwise. Intercepts omitted for brevity. All variables are standardized to a mean of zero and unit standard deviation. Standard errors clustered at the firm and year level.

TABLE 5

Robustness tests

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|   | Market-adjusted CAR | Market-model adjusted CAR | Alternative measure of revisions | Removing outliers | Revisions per unit of uncertainty |
|   | Estimate | p | Estimate | p | Estimate | p | Estimate | p | Estimate | p |
| |∆EPS|\*Covid | 0.001 | 0.000 | 0.001 | 0.000 | 0.006 | 0.009 | 0.004 | 0.000 | 0.010 | 0.000 |
| |∆SAL|\*Covid | 0.000 | 0.469 | 0.000 | 0.871 | -0.001 | 0.631 | 0.001 | 0.769 | 0.003 | 0.000 |
| |∆CPS|\*Covid | 0.001 | 0.000 | 0.001 | 0.000 | 0.058 | 0.000 | 0.006 | 0.092 | 0.012 | 0.000 |
| |∆DPS|\*Covid | 0.000 | 0.010 | 0.000 | 0.001 | 0.085 | 0.000 | 0.028 | 0.003 | 0.004 | 0.070 |
| |∆REC|\*Covid | 0.000 | 0.043 | 0.000 | 0.001 | 0.003 | 0.003 | 0.004 | 0.000 | 0.009 | 0.000 |
| |∆TP|\*Covid | -0.001 | 0.000 | -0.001 | 0.000 | -0.011 | 0.000 | -0.005 | 0.007 | -0.001 | 0.137 |
| |∆EPS| | 0.001 | 0.000 | 0.001 | 0.000 | 0.024 | 0.000 | 0.001 | 0.090 | -0.001 | 0.010 |
| |∆SAL| | 0.001 | 0.000 | 0.001 | 0.000 | -0.004 | 0.095 | -0.006 | 0.023 | 0.000 | 0.242 |
| |∆CPS| | 0.000 | 0.292 | 0.000 | 0.472 | -0.007 | 0.007 | 0.000 | 0.826 | 0.000 | 0.556 |
| |∆DPS| | 0.000 | 0.521 | 0.000 | 0.405 | 0.026 | 0.112 | 0.006 | 0.248 | 0.001 | 0.617 |
| |∆REC| | 0.001 | 0.000 | 0.000 | 0.000 | 0.002 | 0.001 | -0.001 | 0.057 | 0.000 | 0.658 |
| |∆TP| | 0.013 | 0.000 | 0.010 | 0.000 | 0.066 | 0.000 | 0.033 | 0.000 | 0.020 | 0.000 |
| Ret vol |  |  |  |  |  |  |  |   | 2.965 | 0.000 |
| Year effects | Yes |  | Yes |  | Yes |  | Yes |  | Yes |  |
| Quarter effect | Yes |  | Yes |  | Yes |  | Yes |  | Yes |  |
| Firm effects | Yes |  | Yes |  | Yes |  | Yes |  | Yes |  |
| N | 445561 |  | 445561 |  | 445561 |  | 297078 |  | 445561 |  |
| R2 | 26.52% |   | 27.67% |   | 25.98% |   | 15.12% |   | 26.89% |   |

*Notes:* The table reports equation (3) results where the dependent variable is the three-day CAR centered on the analyst forecast announcement date and the normal return benchmark is the market return (*Market-adjusted CAR*) and the market-model return (*Market-model adjusted CAR*). Column *Alternative measure of revisions* reports price reaction results where we measure forecast revisions for EPS, cash flows and dividends by scaling by 1+the previous forecast. Column *Removing outliers* reports results for the sample where we remove the top and bottom 5% of extreme observations for each forecast revision measure. Column *Revisions per unit of uncertainty* normalize forecast revisions by the volatility of residuals from the Carhart model estimated over prior 100 days.

TABLE 6

Signed revisions

|  |  |  |
| --- | --- | --- |
|   | Estimate | p |
| ∆EPS\*Covid | 0.002 | 0.000 |
| ∆SAL\*Covid | 0.006 | 0.000 |
| ∆CPS\*Covid | 0.000 | 0.853 |
| ∆DPS\*Covid | -0.004 | 0.006 |
| ∆REC\*Covid | 0.001 | 0.004 |
| ∆TP\*Covid | 0.002 | 0.000 |
| ∆EPS | -0.003 | 0.000 |
| ∆SAL | -0.006 | 0.000 |
| ∆CPS | 0.000 | 0.499 |
| ∆DPS | 0.001 | 0.180 |
| ∆REC | -0.001 | 0.000 |
| ∆TP | 0.001 | 0.016 |
| Ret vol | 11.075 | 0.000 |
| Year effects | Yes |  |
| Quarter effect | Yes |  |
| Firm effects | Yes |  |
| N | 445561 |  |
| R2 | 7.15% |   |

*Notes:*  The table reports price reaction regression results where we use signed CAR as the dependent variable and signed forecast revisions normalized by the volatility of residuals from the Carhart model estimated over prior 100 days.

 TABLE 7

Price reactions conditional on Google searches

|  |  |  |
| --- | --- | --- |
|   | Estimate | p |
| |∆EPS|\*Covid\*Google | 0.064 | 0.000 |
| |∆SAL|\*Covid\*Google | 0.115 | 0.018 |
| |∆CPS|\*Covid\*Google | 0.121 | 0.000 |
| |∆DPS|\*Covid\*Google | 0.000 | 0.000 |
| |∆REC|\*Covid\*Google | 0.124 | 0.001 |
| |∆TP|\*Covid\*Google | 0.341 | 0.000 |
| Google | 0.000 | 0.000 |
| Year effects | Yes |  |
| Quarter effect | Yes |  |
| Firm effects | Yes |  |
| N | 442426 |  |
| R2 | 29.30% |   |

*Notes:* The table reports abbreviated price reaction regression results where we interact all variables with *Google*, which is the sum of weekly Google searchers for the terms ‘Covid-19’, ‘Covid’, ‘Covid19’, ‘Coronavirus’, ‘SP500’, and ‘stock market’.

TABLE 8

Analyst information discovery vs. interpretation role

|  |  |  |
| --- | --- | --- |
|  | Estimate | p |
| |∆EPS|\*Pre\_EA | -0.001 | 0.293 |
| |∆EPS| | 0.002 | 0.000 |
| |∆EPS|\*Pre\_EA\*Covid | 0.003 | 0.070 |
| |∆EPS|\*Covid | -0.002 | 0.000 |
| Pre\_EA | -0.025 | 0.000 |
| PRE\_EA\*Covid | 0.004 | 0.003 |
| Year effects | Yes |  |
| Quarter effect | Yes |  |
| Firm effects | Yes |  |
| N | 185522 |  |
| R2 | 32.99% |   |

*Notes:* The 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 is zero otherwise.

1. Traditionally, tail risk reflects the chance that an investment value will move more than three standard deviations from the mean (Kelly and Jiang 2014). [↑](#footnote-ref-1)
2. The quick spread of the virus coupled with the uncertainty on how consumers, governments, and firms will respond to the pandemic resulted in a sudden and market-wide increase in uncertainty. To illustrate, between February 19 and March 23 of 2020, the S&P 500 stock market index lost 33.7%, then surged by 29% between March 24 and April 17. High volatility continued throughout 2020. [↑](#footnote-ref-2)
3. On March 4, 2020, the SEC issued an order providing conditional regulatory relief and assistance to reporting companies impacted by the coronavirus. The order provides companies an additional 45 days to file certain Exchange Act reports (including Form 10-K and Form 10-Q) otherwise due between March 1, 2020 and April 30, 2020 if they satisfy certain conditions. <https://www.sec.gov/news/press-release/2020-74> [↑](#footnote-ref-3)
4. Our conclusions are the same if we designate the start of the pandemic in the beginning of March 2020. [↑](#footnote-ref-4)
5. 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’. [↑](#footnote-ref-5)
6. 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). [↑](#footnote-ref-6)
7. See Da, Engelberg and Gao (2011) for tests validating google searches as information demand measure. Bento, Nguyen, Wing, Lozano-Rojas, Ahn, and Simon (2020) document a 36% spike in google searches for information following public announcements of COVID-19 cases. Costola, Iacopini and Santagiustina (2020) report that google searches associate with stock price volatility in a cross-section of six countries. [↑](#footnote-ref-7)
8. Bloomberg article 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, U.K.’ , see https://www.bloomberg.com/news/articles/2019-12-19/analyst-jobs-vanish-as-a-perfect-storm-hits-wall-street-research. [↑](#footnote-ref-8)
9. Out of 48 papers reviewed by Habib, Hasan and Jiang (2017), only two study the consequences of crash risk. An et al. (2015) investigate the impact of crash risk on a firm’s speed of leverage adjustment [↑](#footnote-ref-9)
10. We cannot reject the null that the number of forecasts each month is similar between 2018 and 2019. [↑](#footnote-ref-10)
11. Because target prices have a 12-month forecast horizon, we do not have actual prices to compute target price forecast errors. [↑](#footnote-ref-11)
12. Because of differences in lervels, EPS revisions will tend to be smaller compared to revenue revisions making unstandardized coefficients less comparable. [↑](#footnote-ref-12)
13. As we control for year effects, we do not include *Covid* variable in the regression. The results are the same when we define *Covid* starting from March 2020. [↑](#footnote-ref-13)
14. For the price reaction regression, we omit the *Missing news dummy* from the set of controls. [↑](#footnote-ref-14)
15. 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.’ [↑](#footnote-ref-15)
16. We calculate this as the sum of coefficients on|∆EPS|×Covid and|∆EPS| dividend by the latter. [↑](#footnote-ref-16)
17. The price-to-sales ratio is more useful in valuation for loss-making firms than the price-to-earnings ratio. [↑](#footnote-ref-17)
18. See https://gs.statcounter.com/search-engine-market-share/all/united-states-of-america [↑](#footnote-ref-18)
19. We 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. Using only searches for ‘stock market’ and ‘SP500’ over the pre-pandemic period to build the *Google* measure and then interacting it with pre-pandemic revisions has no impact on our conclusions. [↑](#footnote-ref-19)
20. We 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. [↑](#footnote-ref-20)