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The Impact of Coronavirus Pandemic Severity on Financial Analyst Earnings Forecasts

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Abstract

This thesis presents an assessment of analysts' forecasting abilities when influenced by the Coronavirus pandemic. In the first study, I document an increase in both pessimism and accuracy of earning forecasts issued by analysts during the post-COVID pandemic. I then introduce the primary focus of the thesis, examining the effect of COVID severity levels on analysts' performance, proxied by the key characteristics of earning forecasts: pessimism, accuracy, timeliness and frequency. In the final study, I examine the impact of working from home during the COVID pandemic and find it has no meaningful influence on analysts' performance aside from their sentiment. My studies corroborate and extend the extant behavioural finance and psychology literature, highlighting the importance of understanding the severity of an exogenous shock and the influence of working environments on analysts' performance.

Declaration

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written byanother person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint award of this degree.

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Signature: Hoang Long Bui Date: 16 February 2023

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1. Introduction

1.1. The significance of financial analysts

Financial analysts have long been recognized as important intermediaries who play an essential role in disseminating financial information and evaluating assets in capital markets. They are often perceived as highly-skilled and knowledgeable individuals who constantly provide forecasts and recommendations on firms. Along with auditors, regulators, and other intermediaries in the capital market, financial analysts facilitate and maintain the flow of information, thereby bridging the information gap between firms and investors. In addition, analysts enhance market liquidity, capital allocation and investor confidence by providing firm-specific valuations and forecasting activities, through which they convey their private information and research into prices (Clatworthy and Lee 2017). Analysts from large brokerage firms, which comprise a substantial segment of the financial services sector, are regularly interviewed, and their forecasts and recommendations are quoted in newspapers and social media. Market participants, especially individual investors, will then incorporate this information to make informed investment choices. It is without a doubt that their importance only rises as time goes by.

Given the role of financial analysts, the literature on their impact is unsurprisingly vast. For example, while early research by Givoly and Lakonishok (1979) shows that quick responses to analysts' forecasts potentially give rise to abnormal returns, Barth and Hutton (2004) also find analysts' recommendations-based strategy is likely to generate unusually large profits. In addition, Piotroski and Roulstone (2004) find a positive association between stock return synchronicity and analyst activity, while Kim et al. (2019) observe a huge increase in a firm's ex-ante expected crash risk following an exogenous decline in analyst coverage. Overall, these findings suggest that investors recognize financial analysts' vital informational role; thus, their presence and activities influence the underlying stock market.

Analysts' influence is not limited to individual investors but extends to the companies and their management. For example, Puffer and Weintrop (1991) argue that analysts' forecasts considerably influence the board's expectations of the executives' performance. Subsequently, Kinney et al. (2002) and Roychowdhury (2006) show that top managers have a tendency to make "purposeful interventions" to match or exceed analysts' earnings expectations, thereby avoiding investors penalizing the firms with earnings shortfalls and lowering employment risk (e.g., Beneish 1999, Bartov et al. 2002).

Nevertheless, financial analysts have been increasingly criticized for their lack of objectivity and rigour despite their significance in the capital markets. Many studies have looked into this aspect and generally identify two factors influencing analysts' objectivity in earning forecasts and recommendations: conflict of interest and cognitive factors. Regarding the classic conflict of interest argument, Hayward and Boeker (1998) find that analysts tend to issue more optimistic estimates for firms having investment banking relationships with their brokerage house. Also, Hong and Kubik (2003) imply that analysts can increase their status by consistently providing optimistic forecasts since they will be more likely to be hired by more prestigious brokerages.

The cognitive factor, which has been extensively studied by the extant literature, is the other factor that may greatly influence analysts' objectivity. For example, over-optimism bias, which refers to "an overestimation/underestimation of favourable/unfavourable performance" (Heaton 2002), is widely cited in behavioural finance literature. Cen et al. (2013) also highlight the anchoring bias, suggesting that many financial analysts fail to weigh new information correctly, eventually generating higher forecast errors. Some other commonly studied biases in analysts are overconfidence (Kafayat 2014) and representativeness (Mokoteli et al. 2006).

Despite the ever-growing literature on financial analysts, it lacks an understanding of how the context and environment they work in influence their decision process. The Coronavirus outbreak, though a very unfortunate event, provides a unique opportunity to study how an exogenous adverse event may impact analysts' performance, thereby complementing and extending this vein of literature. The following section will give a glimpse into this pandemic.

1.2. The Coronavirus outbreak

The Coronavirus (otherwise known as COVID-19 or COVID) emerged in late 2019 as a local disease, then quickly spread out worldwide, turning into a global pandemic as declared by the World Health Organisation (WHO) in early 2020. In late-February 2020, the U.S. government eventually declared a public health emergency, at which time the COVID pandemic had infected nearly 10,000 cases worldwide (AJMC 2021). Since then, the novel pandemic has caused massive consequences to all nations, which are yet to show any sign of ending. Figure 1 shows the data timeline on 7-day average cases and deaths in the U.S. since 2020, underlining the significance and persistence of this pandemic. As of this writing, almost 100 million infected cases and over 1 million deaths have been recorded in the U.S. alone, making it among the deadliest calamities ever in modern human history (WHO 2022).

[Insert Figure 1 here]

Nevertheless, mortality and morbidity are not the only concern of this pandemic. COVID-19 has also caused devastating socio-economic impacts, posing unprecedented challenges to governments, businesses and citizens worldwide. While its consequences may vary from country to country, the pandemic generally increases inequality and the gap between the poor and the rich (UNDP n.d.). During the outbreak, self-isolation, social distancing and travel restrictions are put in place to control the spread of the virus, causing massive shocks to consumer spending and business supply in America. While many employees have to work from home, other less fortunate individuals remain sidelined or have to shut down their businesses. According to Crump et al. (2022), the unemployment rate in April 2020 jumped to the highest ever since 1930, while small businesses' aggregate revenues were down by 20% from January to August, resulting in two consecutive quarters of declines in GDP during the first half of 2020. It is estimated that COVID-19 would cost America around $16 trillion, attributable to financial and health-related damages.

Given the significance of Coronavirus and financial analysts, examining their performance during the pandemic is strongly advocated. The following section will provide a brief literature review, thenceforth highlighting the gap in the extant literature. I will then present a summary of my research, which focuses on examining the effect of COVID-19 on characteristics of financial analysts' earnings forecasts, along with two other sub-studies.

1.3. A brief review and the gap in the literature

A considerable body of research has contributed to studying financial analysts and their monitoring activities, with key topics of ongoing interest in areas such as the determinants of their performance (e.g. Clement 1999, Brown et al. 2015), analysts' decision processes (e.g. Block 1999, Hirst et al. 2004), and the informativeness of their outputs (e.g. Brown 1993, Ertimur and Parsons 2011). More recently, a growing body of literature has shifted attention to the impact of the working environment or exogenous shocks on analysts' sentiment and performance, commonly measured by the accuracy of earning forecasts.

In particular, Dehaan et al. (2017) find that unpleasant weather conditions, such as clouds, winds and rains, reduce analysts' activity and induce higher pessimism. Similarly, Dong and Heo (2013) show that analysts' forecasts become less accurate when faced with limited attention caused by influenza epidemics, while Chen (2021) observes more pessimistic forecasts made by sell-side analysts experiencing lunar eclipses. On the other hand, even though Cuculiza et al. (2021) also find terrorism-induced pessimism among affected analysts, he documents a positive impact on analysts' forecast accuracy. This finding also corroborates many previous studies, such as Butler and Lang (1991) and Hong and Kubik (2003), who demonstrate that more pessimistic analysts are associated with higher forecast accuracy. Likewise, Bourveau and Law (2021) find that a life-threatening weather event (i.e., Hurricane Katrina) results in analysts providing more pessimistic forecasts, with no difference in the number of forecasts issued.

Seemingly, although papers studying exogenous adverse events and financial analysts agree that these occasions induce higher pessimism, their impact on analysts' forecast properties remains ambiguous. Not to mention, to my best knowledge, no research has been done to examine the effects of different severities of a negative shock on analysts' performance, especially for such a large-scale calamity as the Coronavirus pandemic.

Given the significance of financial analysts and COVID-19, this thesis aims to address that question by analyzing the four characteristics of analysts' earning forecasts: pessimism, forecast accuracy, timeliness and frequency, as a proxy for their performance during the COVID outbreak. By studying all four properties of forecasts simultaneously, I hope to solve the puzzle remaining in the extant literature.

1.4. Summary of the research

As aforementioned, the main scope of this research is to examine the extent to which the characteristics of analysts' earnings forecasts, namely, pessimism, forecast accuracy, timeliness, and frequency, are moderated by the COVID severity levels. Nevertheless, before answering this question, I have to undertake a ‘preliminary’ study, which aims to verify the pandemic's overall effects on analysts’ performance, i.e. whether there is any significant change in their forecasting ability relative to the pre-pandemic period. In addition, as many individuals are obligated to work from home (hereinafter WFH) during the pandemic, I construct another sub-study, investigating the impact of remote working, alongside the pandemic, on analysts' forecasts. As a result, I will present two sub-studies contributing to this thesis's primary research question.

It is worth noting that forecast pessimism and accuracy, instead of stock recommendations, are the main studied properties in this thesis, just like many previous papers. First, it’s been widely cited that analysts’ sentiment and their output are associated, underlining the potential influence of the surrounding context on their performance (e.g. Nguyen 2019, Cuculiza et al. 2021). Second, since earning forecasts are inputs to stock recommendations, more precise predictions will eventually lead to more profitable stock recommendations. Also, while many articles have found a positive association between forecast accuracy and job security or career advancement, they don't see any relation between the profitability of stock recommendations and analyst turnover (Mikhail et al. 1999, Hong and Rubik 2003). This finding suggests that financial analysts may be incentivized to concentrate on forecast accuracy rather than stock recommendations, hence a more valuable variable for academics to explore.

1.4.1. Sub-study 1: the overall impact of Coronavirus on forecasts' properties

This study investigates whether the Coronavirus has any effect on analysts' sentiment and accuracy, i.e. whether there is any significant change in these two characteristics after the pandemic emerged in the U.S. The research question is motivated by the fact that financial analysts are subject to a wide range of cognitive factors, thereby increasing the likelihood of issuing subjective predictions following an exogenous shock.

A commonly cited bias among analysts is optimism, provoked by "an intention to deceive, not to issue a report with negative forecasts, or by the fact that there is a failure in the processing of the available information" (Francis et al. 1997). And yet, in many cases, analysts become optimistically biased due to conflicts of interest arising from either remuneration/compensation structure (Michaely and Womack 1999, Hong and Kubik 2003) or building relationships with executives and gaining access to private information (Lim 2001, Richardson et al. 2004). In either case, these findings suggest that analysts have incentives to adjust their forecasts intentionally to their favour during the pandemic.

Similarly, a growing body of literature has shown that exogenous adverse events can impact analysts' forecasting activity. While Nguyen (2019) argues that critical life events, namely job transitions, negatively alter analysts' behaviours and cause forecast pessimism, Cuculiza et al. (2021) find that terrorism induces pessimism to analysts local to the attacks, consequently affecting their performance. Dehaan et al. (2017) and Bourveau and Law (2021) find similar results when studying the effects of unpleasant and life-threatening weather events, respectively. These findings, together with the fact that analysts are subject to various biases, raise the question of whether COVID-19 causes a significant change in their forecasting performance.

I investigate answers to this question by utilizing ordinary least-square (OLS) regressions on a sample of 401,427 earning forecasts issued during 2019-2020. The variable of interest is *Post_Covid*, an indicator variable equal to 1 if an earning forecast is issued after February 2020, when COVID-19 emerged in America. The independent variables are *Pessimism* and *PMAFE*, measuring forecast pessimism and accuracy, respectively. The regression results indicate significant changes across all tests. Specifically, relative to the pre-pandemic period, analysts become more pessimistic yet, at the same time, more accurate.

1.4.2. Main study: the impact of COVID severity levels on forecasts' characteristics

After determining that COVID-19 affects analysts' sentiment and accuracy, I now present my primary research: to which extent the COVID severity levels moderate the characteristics of earning forecasts. This research question is motivated by the theoretical framework known as the "affect heuristic", which states that individuals rely heavily on their affective feelings to guide judgements and decisions, leading them to be irrational in some situations. As I propose that a higher COVID severity level will cause higher pessimism, the theory suggests this will simultaneously provoke more sizeable variations in analysts' performance relative to low severity.

As aforementioned, to date, there hasn't been any paper that investigates the impact of different severity levels of an exogenous adverse event on analysts' performance. That said, by reviewing a body of psychological literature, Seta and Seta (2019) point out that people may generate more negative responses when exposed to a more adverse event, of which the research experimentally controls for the stressing content. Likewise, Bernile et al. (2016) emphasize that an adverse event may affect highly-skilled professionals differently according to its intensity level by showing that CEOs who experienced natural disasters with extreme downside outcomes behave more conservatively than those who witnessed similar events without extremely negative consequences. Therefore, as the severity of the COVID pandemic changes over time and by location, it raises concerns about how analysts' sentiment and performance vary as the pandemic progresses during 2019-2020.

I conduct the research into this question by running OLS regressions across the key characteristics of earning forecasts using the same sample as in the first sub-study. However, the variable of interest this time is the *HiCOVID*, an indicator variable equal to 1 if the COVID severity state level on the day a forecast is issued is high and 0 otherwise. Besides *Pessimism* and *PMAFE*, the independent variables also include *Speed* for timeliness and *Frequency* for the number of estimates given in a period. Seemingly, as the COVID severity level escalates, analysts tend to be more pessimistic, more accurate and less timely, but indifferent in the number of forecasts issued each quarter, providing evidence of an effect from the pandemic.

1.4.3. Sub-study 2: the impact of WFH on analysts' performance

Another significant effect caused by the COVID pandemic is that individuals in nonessential services have to telecommute to avoid spreading the illness in society. For most affected employees, this would be the first time they have to work away from the office. This occurrence calls into question whether job efficiency is maintained during this unprecedented time. Even though the literature on this topic is well-established, the findings of WFH's impact on performance remain relatively ambiguous.

Specifically, Tietze and Nadin (2011) and Sardeshmukh et al. (2012) find an association between working from home (WFH) and less time pressure and greater autonomy, resulting in less job exhaustion. Meanwhile, Ford and Butts (1991) and Lupu (2017) assert that increased autonomy and flexibility are two critical factors that lead to job satisfaction, implying that WFH will lead to higher efficiency. In contrast, many other studies agree that disconnection from colleagues, isolation and family distractions could deteriorate work output when telecommuting (e.g. Gajendran and Harrison 2007, DeGray 2012, Sutherland 2015). The research findings in this body of literature are seemingly split into two contrasting sides.

Not to mention, WFH during COVID-19 is different from WFH before the pandemic. Under the influence of the Coronavirus, exploring the implications of WFH will be even more complex. It is possible that any positive effects of WFH on mental health will be cancelled out by the impact of COVID-19. Alternatively, if WFH results in negative consequences, they may be amplified by the progress of the Coronavirus.

Motivated by this ambiguity and the fact that there has not been any paper that specifically investigates analysts working from home, I explore answers to this question by adding another indicator variable, *WFH*. This indicator variable equals one if an earning forecast is issued during the period the highest stay-at-home order is imposed in the state the analyst is working. I also add another interaction term to capture any interaction effect between WFH and COVID severity levels.

The regression output shows that, although WFH significantly affects pessimism, it does not influence forecast accuracy, timeliness and frequency. One possible reason is that analysts are highly skilled and educated, so they adapt to new changes quickly and effectively. My findings give rise to the WFH trend following the COVID pandemic and how brokerage firms should work towards tailoring analysts' working environment to bring the best out of them.

2. The overall impact of COVID on financial analysts' performance

2.1. Introduction

This chapter's objective is to examine how the sentiment and accuracy of analysts are impacted as the COVID pandemic emerges in the U.S. The research question is motivated by the literature on financial analysts, indicating that they have incentives to generate subjective forecasts due to a range of cognitive biases and that their sentiment can be affected by exogenous adverse events. At the same time, a growing body of literature has indicated that individuals' sentiment is associated with job performance, urging an investigation into analysts' forecasting activity during the COVID pandemic.

Meanwhile, the onset of Coronavirus is unique in two senses. First, the pandemic has shattered people's norms worldwide, putting millions of lives at risk and hitting all economies upside down. Nonessential services like schools and recreational activities are shut down, and face-to-face interactions are reduced to minimal to cope with the spread of the virus. As a result, the consequences of the virus are not limited to livelihoods and economic damage but also mental health. Second, COVID-19, though a very unfortunate event, creates a once-in-a-while opportunity to study how analysts make decisions in a challenging environment with high uncertainty.

There is strong evidence that such a calamity as COVID-19 will likely cause negative sentiment among analysts, which in turn affects their ability to forecast and make rational decisions. During lockdowns, people become more uncertain and unable to plan for the future, are required to isolate themselves, and hence unable to carry out social meetings, leading to a higher degree of negative sentiment. According to a global report by Qualtrics on more than 2000 employees in seven countries, 42% suffered a decrease in overall mental health, 53% felt sadness daily, and 76% saw an increased level of stress during 2020 (Qualtrics, 2020).

At the same time, despite being considered highly skilled and knowledgeable professionals, substantial evidence shows that financial analysts could be among those mentally affected by this large-scale pandemic. For example, Cuculiza et al. (2021) find that terrorism events affect the sentiment and forecasts of local analysts. Similarly, Bourveau and Law (2021) document that a life- Hurricane Katrina, an exogenous shock, causes analysts to be more pessimistic than those who do not suffer from the storm. In another related paper, Nguyen (2019) argues that job transitions negatively impact analysts' behaviours, leading to forecast pessimism.

At the same time, many psychological papers like Lechanoine and Gangi (2020) and Berenbaum (2021) point out that in times of uncertainty, individuals are more likely to be influenced by cognitive and affective biases, like belief, over-confidence and availability bias, leading to irrational thinking and misjudgement. For example, a high degree of uncertainty may lead analysts to herd as they are unsure of their performance against their peers or unconfident in their ability (e.g. Clement and Tse 2005).

Interrelated to this, finance literature also highlights that negative sentiment is linked with reduced job performance. Specifically, an analysis involving 2,264 employees by Boles et al. (2004) indicates that factors such as stress and lack of emotional fulfilment are strongly linked to productivity loss. Similarly, Weakliem and Frenkel (2006) find that lower morale is associated with lower efficiency, while Lerner and Henke (2008) note that depression can cause at-work performance shortfalls.

In light of the substantial evidence in psychology and finance literature, I hypothesize that the emergence of COVID-19 impacts analysts' forecasting accuracy and sentiment. As anecdotal evidence for this hypothesis, Figure 2 shows the percentage of pessimistic forecasts in each quarter for 2019-2020. A forecast is pessimistic if the estimate is below the consensus, following previous papers like Clement (1999), Clement and Tse (2005), and Cuculiza et al. (2019).

[Insert Figure 2 here]

The figure is plotted using a sample of 650,264 forecasts obtained from IBES Detail History and Actuals between 1st January 2019 and 31st December 2020. The percentage is calculated simply as the number of pessimistic forecasts divided by the total earning forecasts in each quarter. Seemingly, throughout 2019, there is a downward trend in pessimistic forecasts, which begins to overturn in Q1 2020. A significant leap is then observed in Q2 2020, peaking at nearly 52% before slightly trending downward again. As COVID-19 broke out around March 2020 in the U.S., figure 2 implies that there might be an association between the pandemic and pessimistic forecasts.

This is, of course, just a preliminary analysis to provide anecdotal evidence about COVID-19's impact. There might be many reasons why analysts issue pessimistic predictions. I now construct empirical regressions to test my hypothesis. The approach is to run OLS regressions on the two key independent variables: *Pessimism and PMAFE.* The first measure, *Pessimism*, is used to capture the pessimism among analysts, while the second one, *PMAFE*, is used to capture the relative accuracy of forecasts. For every regression model, the variable of interest is *Post_Covid*, an indicator variable equal to 1 if an estimate is given after February 2020 (i.e. from March 2020 onwards) and 0 otherwise. Control variables and year- and analyst-fixed effects are included.

The regression outputs indicate that COVID-19 impacts analysts' sentiment and accuracy. On average, relative to the pre-pandemic period, analysts become more pessimistic by roughly 20% (as in the baseline regression). However, quite surprisingly, their accuracy improves at the same time. This finding highlights that COVID-19, as an exogenous adverse event, significantly affects analysts' outputs, thereby taking us to the next research question later on, which examines how the COVID-19 severity level moderates the earnings forecasts' properties.

2.2. Literature review and hypothesis development

As Brauer and Wiersema (2018) point out, there are two competing perspectives regarding financial analysts in the extant finance literature. One argues that analysts are highly skilled professionals who contribute to monitoring capital markets, implying they are not subject to the influence of social context and cognitive biases (e.g. Stickel 1992, Womack 1996). As opposed to this view, many others argue that analysts can sometimes be irrational and subject to biases influencing their forecasting ability (e.g. Amir and Ganzach 1998, Hirschleifer 2015). Over time, the latter perspective seems to be increasingly accepted by academics and the majority over the first.

Dating back to the research by Amir and Ganzach (1998), they find three heuristics that concurrently influence earning forecasts: leniency, representativeness and anchoring. Under these biases, analysts tend to overreact to positive news yet underreact to adverse events. Cen et al. (2013) highlight the anchoring bias again by pointing out that analysts likely issue pessimistic forecasts when a company's forecast earnings per share (EPS) is lower than the industry median. In addition, analysts sometimes tend to be overoptimistic to ensure access to private information and to build relationships with CEOs (Lim 2001, Richardson et al. 2004). Furthermore, their forecasts may be compromised by impression management (Westphal and Graebner 2010), career concerns (Hong, Kubik and Solomon 2000), or compensation structure (Michaely and Womack 1999, Hong and Kubik 2003, O'Brien et al. 2005), leading to analysts ignoring their research and herding to generate more optimistic forecasts.

At the same time, many psychological papers like Lechanoine and Gangi (2020) and Berenbaum (2021) point out that in times of uncertainty, individuals are more likely to be subject to a range of cognitive and affective biases, such as belief, over-confidence and availability bias, which result in irrational thinking and misjudgement. For example, Clement and Tse (2005) find that a high degree of uncertainty may lead analysts to herd as they are unsure of their performance against their peers or unconfident in their ability. Consequently, various cognitive biases can influence analysts' judgements, deviating them from actual estimates and increasing forecast errors (e.g. Hilary and Menzly 2006).

Since it has been widely proven that financial analysts can be irrational and their judgments can be biased, a growing concern about their forecasting activity during this challenging and uncertain time (i.e. COVID-19) is evident. In fact, one of the most concerning channels through which the global health crisis has altered people's daily lives is mental health, which arises from the fear of being infected and restricted from gathering and going out.

An increasing number of studies have extensively reported the detrimental effects of the pandemic on the mental stability and well-being of the population. During lockdowns, people become more uncertain and unable to plan for the future, are required to isolate themselves, and hence unable to carry out social meetings, which very likely leads to a higher degree of negative sentiment. Specifically, according to a global report by Qualtrics on more than 2000 employees in seven countries, 42% suffered a decrease in overall mental health, 53% felt sadness daily, and 76% saw an increased level of stress during 2020 (Qualtrics, 2020). Likewise, surveys conducted by US CDC indicate that adults reporting symptoms of depression in America increase from only 11% for the year 2019 to as high as 42% in December 2020 (Abbott 2021). The growth in the number of people reporting various mental illnesses since the outbreak also appears in surveys conducted worldwide, such as Dawell et al. (2020) in Australia, Pan et al. (2020) in the Netherlands, Son et al. (2020) and Panchal et al. (2021) in the United States.

Despite being considered highly skilled and knowledgeable professionals, substantial evidence shows that financial analysts could be among those mentally affected by this large-scale pandemic. In particular, Cuculiza et al. (2021) conclude that "exogenous and extremely negative events, such as mass shootings and terrorist attacks, influence the sentiment and forecasts" of local analysts. Notably, analysts closer to these attacks tend to issue more pessimistic forecasts than the consensus. Similarly, Bourveau and Law (2021) document that a life-threatening weather event (i.e., Hurricane Katrina) causes analysts to be more risk-averse, resulting in more pessimistic forecasts than those who do not suffer from the storm. Likewise, Dehaan et al. (2017) suggest that unpleasant weather, such as clouds, wind, and rain, is associated with reduced activity and analyst pessimism. In another related paper, Nguyen (2019) argues that critical life events, namely job transitions, negatively alter analysts' behaviours and cause forecast pessimism. Yet, psychological influences may not be the only concerns, as other papers have also identified other factors that likely affect analysts' decisions during the outbreak, such as attitudes towards risks (Zhang et al. 2022) or lack of information access (Hope et al. 2022).

Given the potential influences of COVID-19, the performance of financial analysts during the pandemic needs to be investigated. Indeed, many papers provide evidence of the inverse relationship between negative sentiment and productivity. Weakliem and Frenkel (2006) find that lower morale is associated with lower efficiency, while Lerner and Henke (2008) note that depression can cause at-work performance shortfalls. An analysis involving 2,264 employees by Boles et al. (2004) indicates that factors such as stress and lack of emotional fulfilment are strongly linked to productivity loss. Similar findings are also documented by previous papers such as Goetzel et al. (2004) and Cheema and Asrar-ul-Haq (2017). More importantly, adverse health issues can cause long-term effects in the workplace. After a six-month follow-up of 229 workers, Lerner et al. (2004) suggest that individuals with depression are more likely to undergo job turnover, absenteeism, and presenteeism, which are widely reported to be associated with decreased work outcomes (Johns, 2009).

There is also direct evidence demonstrating that the Coronavirus may affect analysts. For example, Yu (2022) show that analysts' earning forecasts become more pessimistic after the outbreak. Gao et al. (2021) and Zhang et al. (2022) document that lockdowns imposed due to COVID-19 significantly increase analysts' forecast dispersion for companies in pandemic-exposed zones and decrease the number of forecasts. On the other hand, Hao et al. (2022)

indicate that analysts issue timelier, more frequent, but less accurate estimates during 2020. Consequently, given the evidence in the psychology and finance literature aforementioned and the significance of COVID-19, I conjecture that:

Hypothesis 1: the emergence of COVID-19 negatively impacts analysts' sentiment and accuracy.

2.3. Data and methodology

This section describes how I build the data sets and the empirical methodology for this sub-study. The study period starts in January 2019 and ends in December 2020, approximately equivalent to one year before and one year after the emergence of the novel Coronavirus in the United States of America. The final complete sample is used for all subsequent studies in this thesis.

To begin with, I collect data on quarterly earnings-per-share (EPS) forecasts issued by financial analysts from the Institutional Brokers' Estimate System (IBES) database. To avoid the effect of stale forecasts (Jegadeesh et al. 2004), I remove estimates made by unidentified analysts and limit the sample to include EPS forecasts with period indicators of 6 to 9 (one to four quarters ahead). All observations must have data on expected and actual earnings, announcement dates, median and mean estimates, and analyst IDs. After filtering, the sample contains 650,264 estimates, including revisions, generated by 1,268 unique analysts covering 3,580 firms.

One difference in my thesis from other previous studies is that I choose to keep the forecast revisions. For instance, Bourveau and Law (2016) only use the last forecasts, whereas Cowen et al. (2006) use the first estimates issued by analysts. However, since the level of COVID severity in each state changes daily, forecast revisions will also likely be affected. Therefore, I believe that keeping all forecast revisions in the study is appropriate, given that the COVID pandemic is not a short-duration shock.

In the next step, I collect analysts' locations (state of residence) when they publish a forecast using the Refinitiv Eikon software. Specifically, I first download all analysts' reports between 2019 and 2020 from this database. I then narrow my focus to only the top 25 brokerage houses with the highest number of forecasts produced during this period. As a result, the number of observations is reduced from 826,859 to 569,177, from which I obtain analysts' locations by manually looking up the phone numbers provided in the reports. I do not necessarily inspect every report but use a 6-month interval instead. This method allows me to capture changes in an analyst's office location, i.e. the state of residence. Besides reports made by analysts outside America, I remove those without analysts' names or office phone numbers because their places cannot be located, resulting in a sample with 1,806 analysts covering 5,027 unique firms.

After gathering analysts' data, I have to identify analyst IDs for the observations downloaded from Refinitiv Eikon software to match analysts' locations with the forecasts obtained from the IBES Detail History and Actuals. Even though the reports from the Eikon database display analysts' full names, the IBES Detail History and Actuals file only gives analyst codes (ANALYS). Therefore, the IBES Recommendations file, which provides the first and last names of the analysts and the analyst codes, is utilized to facilitate the matching of the earning forecasts file (IBES Detail History and Actuals) with the analysts' locations file (Refinitiv Eikon). My final dataset consists of 401,427 observations with 771 different analysts covering 3,104 firms from 2019-2020. Table 1 presents a summary of my sample selection procedure.

[Insert Table 1 here]

To test the first hypothesis, i.e. whether the Coronavirus negatively impacts analysts' pessimism and accuracy, I propose the following OLS models:

$$Pessimism_{i,j,t} = \alpha + \beta_1 Post\_Covid + Controls + FEs \quad (1a)$$

$$PMAFE_{i,j,t} = \alpha + \beta_1 Post\_Covid + Controls + FEs \quad (1b)$$

where *Pessimism* is the measure of analysts' sentiment, a dummy variable equal to one if an estimate by analyst *i* is less than the latest consensus forecast for the same firm *j* and the same forecast period end date, following Cowen et al. (2006). I use consensus forecasts from the IBES Summary File because they are less subject to IBES's subsequent revisions than those in IBES Detail History (Bourveau and Law 2021).

Next, I capture forecast accuracy by using the proportional median absolute forecast error (PMAFE), following Clement (1999) and Cuculiza (2021). This method calculates relative forecast accuracy, allowing comparisons between different analysts covering the same firm in the same quarter. Another advantage of PMAFE is that it controls company-time fixed effects, as Clement (1999) claims. The equation for PMAFE is as follows:

$$PMAFE_{i,j,t} = \frac{AFE_{i,j,t} - \overline{AFE_{J,t}}}{\overline{AFE_{J,t}}} \quad (2a)$$

$$AFE_{i,j,t} = \left| AF_{i,j,t} - RE_{i,j,t} \right| \quad (2b)$$

where PMAFE is the difference between an analyst's absolute forecast error ($AFE_{i,j,t}$) and the average absolute forecast errors of all analysts covering the same firm *j* during the same period t ($\overline{AFE_{J,t}}$), scaled by $\overline{AFE_{J,t}}$ to alleviate heteroskedasticity (Clement 1999). *AFE* represents analysts' EPS forecasts, and *RE* is the firm's realized (actual) EPS. A simple interpretation of this equation is that a negative PMAFE indicates that an analyst performs better than the average, and a positive value suggests otherwise.

Following prior research, a set of control variables for several characteristics of analysts is employed. In particular, *Portfolio – Firms* and *Industry_covered* represent the number of firms and industries analyst i covers in quarter t, respectively. *GExp* is the general experience, the years between a forecast's date and when an analyst starts a financial job. My definition of *GExp* is generally broader than some papers, which define it as the number of years since the first date an analyst releases a forecast for any company in the IBES database (see Cuculiza et al. 2021). However, I argue that previous financial job experiences, such as investment or risk analysts, can likely affect the skills and mindset of an equity analyst. Therefore, these experiences should also be taken into account. I collect this information using LinkedIn and BrokerCheck's website, which provides snapshots of brokers' employment history in the U.S.

Furthermore, experience in a specific company is also vital. Hence, I include a variable *Firm_Exp*, the number of years since an analyst first covered a firm until the forecast date. I also control *Forecast Age*, a proxy for the number of days between the forecast and earnings announcement date for firm j, as Clement (1999) points out its effect on forecast accuracy. Furthermore, I include an indicator variable, *Top10 Estimator*, which is equal to 1 if the brokerage house the analyst i is working for is in the top 10 of the 2021 All-America Research Team Rankings by Institutional Investors, following Jacob et al. (1999). Lastly, I set another dummy variable, *Male*, equal to 1 if the analyst i is a male and 0 otherwise.

In addition to these control variables, I include the fixed effect of the analyst to absorb any time-invariant unobserved analyst characteristics (like innate ability) and identify any systematic difference between analysts in the dependent variable. Also, using the analyst fixed effect helps capture the impact of COVID within analysts.

2.4. Empirical results

2.4.1. Summary statistics

The summary statistics for the variables in my model are reported in Panel A of Table 2. The mean of the dependent variable, *Pessimism*, is 0.39, which implies that nearly 40% of the total forecasts are relatively optimistic during the study horizon. On average, analysts in my sample data have 17.61 years of general experience and 5.16 years of firm experience. They cover approximately 20 firms across five industries in each quarter. Lastly, 90% of the analysts in the sample are male.

[Insert Table 2 – Panels A and B here]

Additionally, I construct a correlation matrix reported in Table 3 to highlight any multicollinearity issue. The outcome indicates either insignificant or inconsiderable coefficients between studied variables, hence minimizing multicollinearity concerns.

[Insert Tables 3 here]

2.4.2. COVID-19's impact on analysts' sentiment and accuracy

This section presents my findings for the first sub-study, i.e. whether COVID-19 impacts analysts' sentiment and accuracy. The empirical results of this study are reported in Table 4. Consistent with many prior studies, I find that as an exogenous shock, COVID-19 negatively impacts analysts' sentiment.

[Insert Table 4 here]

Controlling for analysts' characteristics, it is evident that relative to the pre-pandemic period, analysts seem to be more pessimistic, roughly by 20% (Table 4 - column 1). The result remains significant when adding analyst fixed effect and under the Probit and Logit tests.

Interestingly though, as the estimates of *Post_Covid* on *PMAFE* are all significantly negative, analysts' accuracy over the same period seems to increase, probably due to the pandemic-induced pessimism.

Overall, my first sub-study indicates that the Coronavirus outbreak influences analysts' sentiment and accuracy, but its consequence is not always negative. Although this finding may sound surprising initially, it is consistent with several prior studies, like Cuculiza et al. (2021), who argue that terrorism-induced pessimism leads to lower forecast errors.

3. The impact of COVID-19 severity levels on analysts' performance

3.1. Introduction

This chapter presents the major study of my thesis, i.e. the impact of different COVID-19 severity levels on analysts' performance. This research is contingent on the previous sub-study, in which I first have to determine the overall effect of COVID-19 on analysts' forecasts. As that effect has been validated, I now focus on examining how COVID-19 severity levels moderate analysts' performance. The research is motivated by the theoretical framework known as the "affect heuristic", which suggests that individuals may sometimes rely too heavily on their emotions to make judgements, leading to irrational decisions eventually (Slovic et al. 2007).

Accordingly, in this research, I directly account for the fact that individuals may not react the same to different intensity levels of an unfavourable event since their affective feelings may escalate along with the occasion. As in the previous sub-study, I document that the unexpected COVID-19 influences analysts' performance, proxied by the four characteristics of earning forecasts. This finding is consistent with prior papers, which all suggest that an exogenous adverse event would cause negative impacts on analysts, especially their sentiment (e.g.

Bourveau and Law 2021, Cuculiza et al. 2021). However, the nature of COVID-19 is different from a terrorist attack or a hurricane. The Coronavirus is a long-lasting pandemic with severity levels changing daily across each state, while other events last for only one or days at most. Figure 3A displays the COVID-19 Death Rate in the US by state (deaths per 100,000) since 21st January 2020.

[Insert Figure 3A here]

As can be seen, as time goes by, the COVID death rate varies vastly from state to state, indicating the COVID severity can be unique across locations. As a result, analysts in different states may react unequally to the COVID pandemic at a given time, making their performance even more unpredictable. In fact, an increasing number of papers emphasize the importance of affect in human judgement and decision-making. While Seta and Seta (2019) demonstrate that people manifest more negative responses when exposed to a more highly adverse event, Bernile et al. (2016) emphasize that an adverse event may affect highly-skilled professionals like CEOs differently according to its intensity level. Therefore, as the severity of the COVID pandemic changes over time and by location, it motivates my research to investigate how analysts' performance varies as the pandemic progresses.

Similar to my first sub-study, I will investigate this question using OLS regressions. One considerable change, though, is that I will examine the effect of COVID-19 severity levels on not two but four characteristics of earning forecasts: pessimism, accuracy, timeliness and frequency. Since the pandemic is very distinct in its nature, posing unprecedented challenges to individuals worldwide, I want to grasp this opportunity to provide a comprehensive assessment of analysts’ performance, proxied by four different properties of forecasts.

The key explanatory variable in this research question is *HiCOVID*, a dummy variable equal to one if the COVID severity level on the day a forecast is generated is high. The severity of COVID levels is defined as per US CDC's guidelines[1]. Generally, the severity is measured at the state level and is said to be high when new cases per 100,000 population over the past 28 days are more than 100. Year- and analyst-fixed effects and more control variables are included in regressions.

The regression outputs indicate that as COVID-19 gets more severe, analysts become more pessimistic and more accurate yet issue forecasts in a less timely manner. I find no difference in the number of estimates given in each quarter. The findings suggest that the COVID severity levels indeed moderate analysts' performance, proxied by the four characteristics of earning forecasts, thereby highlighting the affect heuristic among analysts and the importance of examining an event's intensity levels.

3.2. Literature review and hypothesis development

A considerable number of studies in psychology literature show that exposure to an event with higher intensity may result in more profound reactions. In particular, Seta and Seta (2019) construct a review of the literature concerning individuals' affective responses to adverse life experiences on two levels: highly and mildly negative. They find that participants react more intensely when faced with similar events but less extremely if exposed to events with different levels. Likewise, Bernile et al. (2016) show a "non-monotonic relation between the intensity of CEOs' early-life exposure to natural disasters and subsequent corporate risk-taking". Specifically, they find that CEOs exposed to natural disasters without extreme downside lead firms in a more aggressive way than those who experienced highly negative consequences. Similarly, Castillo and Carter (2011) find heterogeneity of behaviour among populations affected by Hurricane Mitch in 1998, suggesting that catastrophic events may alter behaviours

[1] US CDC – US Centres for Disease Control and Prevention: a national public health agency of the U.S.

differently according to the severity of the shock. Generally, the findings of these papers consolidate the "affect heuristic" theory, which suggests that individuals' judgements rely heavily on their emotions and hence may become more irrational if an abrupt event deteriorates.

Meanwhile, the severity level of COVID-19 changes daily according to the number of infected cases, hospitalized victims and deaths in each state of the U.S. Since the severity increases, the authority has to tighten restrictions and impose stricter regulations. As Aknin et al. (2022) assess the mental health of the population from 15 countries, they find that higher policy stringency and pandemic intensity, measured by deaths per 100,000 inhabitants, are both associated with lower mental stability and life happiness. Similarly, Le and Nguyen (2021) discover a positive relationship between COVID-19 severity, measured by mortality rate, and daily anxiety, worry, displeasure and depression in the U.S.

Seemingly, there is substantial evidence that analysts' mental health and COVID severity level are positively associated. I thereby propose my first hypothesis for this study as follows:

Hypothesis 2a: The level of pessimism in analysts' forecasts is moderated by the severity of COVID-19 at the state level.

As for forecast timeliness, previous studies consistently indicate the negative relationship between an adverse event and this characteristic of earning forecast. Dehaan et al. (2017) observe that forecast delays are highly correlated with unpleasant weather conditions. Similarly, Nguyen (2019) discovers a reduction of 16% in the timeliness of earnings forecasts from analysts who recently switched jobs. Driskill et al. (2020) find that limited attention, a cognitive bias that likely occurs during the COVID pandemic, adversely impacts analysts' forecast timeliness. More recently, Du (2021) explores that analysts are less likely to issue timely forecasts, especially female forecasters, during lockdowns. Based on the firm evidence of previous studies, the following hypothesis is proposed:

Hypothesis 2b: Financial analysts issue less timely forecasts as the COVID's severity within their state exacerbates.

Although the aforementioned papers share consistent forecast timeliness findings, their conclusions regarding forecast accuracy remain conflicting. On the one hand, Dehaan et al. (2017) and Nguyen (2019) argue that sentiment-induced pessimism is more likely to reduce analysts' performance in terms of forecast accuracy. Their findings complement those in the broader psychological literature that constantly substantiate the negative relationship between pessimism and work outcomes (see Tuten and Neidermeyer 2004, Kour et al. 2019, Kenneally 2020). On the other hand, Cuculiza et al. (2021) assert that analysts affected by terrorists are more accurate than the average analyst, implying that individuals with higher levels of pessimism produce better forecasts. This claim is also supported by Hugon and Muslu (2010) and Jiang et al. (2016). They show that relatively more pessimistic analysts provide more accurate forecasts because their estimates are systematically lower than the consensus. Particularly, Anglin et al. (2021) find that analysts' forecast errors and dispersion increases along with the COVID's severity, though they only examine forecasts on REITs. As for the last property of earning forecasts, forecast frequency, while Bourveau and Law (2021) find no difference in the number of forecasts affected by hurricanes, Dehaan et al. (2017) show that analysts issue fewer revisions when facing unfavourable local weather.

It is worth noting again that, to my best knowledge, no paper has specifically examined the effect of varying severity levels of an exogenous event on analysts' forecasting activity. As a result, although many related articles support hypotheses 2a and 2b, it is unclear how COVID severity levels moderate the forecasts' accuracy and frequency. Drawing on the conflicting evidence on forecast accuracy and frequency, the extent to which the COVID pandemic impacts these two characteristics remains a critical empirical question, and thus I conjecture the following:

Hypothesis 2c: The accuracy and frequency of the financial analysts' forecasts are impacted proportionally to the COVID levels.

3.3. Data and methodology

The sample data remains the same as in the first sub-study (Chapter 2.3). However, for this research question, I have to obtain information on the severity of COVID across states and time from the US CDC website. This federal agency employs four levels of severity of COVID and records them daily for each U.S. state since 1st January 2020. I then match this information with our sample data. Our final dataset consists of 401,427 observations with 771 different analysts covering 3,104 firms during 2019-2020. The distribution of earning forecasts across states, years, and different severity levels is shown in Figure 3B.

[Insert Figure 3B here]

To my best knowledge, the most recent research that collects analysts' locations was published in 2021, yet their study period is before 2016, and hence the data is likely obsolete by the current date. Therefore, as of the writing of this paper, I believe my data contain the most up-to-date information relating to financial analysts in the U.S., especially their working locations.

To examine the extent to which COVID severity levels moderate the characteristics of earning forecasts, I propose an OLS regression similar to model (1):

$$Forecast\ properties_{i,j,t} = \alpha + \beta_1 HiCOVID + Controls + FEs \qquad (4)$$

where i, j, and t denote analysts, firms, and quarters, respectively. The dependent variable is the *Forecast properties*, the placeholder for pessimism, accuracy, timeliness and frequency.

The measuring methods for pessimism and accuracy remain the same as in the previous sub-study (see Chapter 2.3).

I evaluate the forecast timeliness using the variable *Speed*, following Nguyen (2019). Specifically, I first normalize timeliness by assigning ranks to all analysts based on the order in which they release the first forecast after the announcement date for the same firm within the same forecast period. Therefore, the sample for this conjecture will exclude all forecast revisions. The analyst who issues the earliest forecast receives the lowest rank (i.e. rank 1). Then I estimate *Speed* using the following equation:

$$Speed = 100 - \left[\frac{Rank - 1}{Number\ of\ analysts - 1}\right] \times 100 \qquad (5)$$

where the variable *Number of analysts* in the denominator indicates how many analysts issue forecasts for the same firm in one forecast period. A higher *Speed* value reveals an analyst with higher forecast timeliness. Lastly, I use *Frequency* to capture the total number of estimates issued by each analyst in each quarter, including revisions, following Bourveau and Law (2021).

The critical difference in this research relative to my first sub-study is the variable of interest. The key explanatory variable this time is *HiCOVID*, a dummy variable representing the risk levels of COVID in each state for every day since the outbreak. According to the US CDC's website, there are four stages of COVID: green when new cases per 100,000 population over the past 28 days are less than 50, yellow when it is between 50 and 99, orange when new cases are from 100 to 500, and red when it is above 500. Within the scope of this paper, we redefine the COVID risks to two categories only: *Low* for green and yellow, and *High* for orange and red. The dummy variable *HiCOVID* is equal to 1 if the level of risk within a state on a specific date is high and 0 otherwise.

Other control variables remain the same as in the first sub-study. Aside from the analyst-fixed effect described in Chapter 2.3, I also include the year dummy to determine any time trends (time-series variations) in the dependent variable by controlling for macroeconomic factors that likely affect analysts' performance.

Another important consideration is the regressions on forecast frequency. Since the forecast frequency is the number of forecasts in a quarter, some modifications are needed. First, the variable of interest is *quar_HiCOVID*, an indicator variable equal to one if the average COVID level in that quarter is high. Second, for continuous control variables (e.g. *GExp, Portfolio_firms*), I also have to take their averages in that quarter, except for *Firm_Exp*, which is left out in this regression since forecast frequency is likely not contingent on any specific firm.

3.4. Empirical results

3.4.1. COVID severity level and analysts' sentiment

I now turn to discuss the main specification of this research. I test hypothesis 2a using the proposed OLS model and report the estimates for my regression in Table 5. Specifically, I examine whether financial analysts become more pessimistic as COVID progresses and becomes more severe. Consistent with the first conjecture, the variable of interest *HiCOVID* is significantly positive, suggesting that analysts are more likely to issue more pessimistic forecasts than average analysts as the COVID risk level gets more severe.

In the first column, I run the regression without any fixed effects and find that the coefficient of *HiCOVID* is 0.1461, implying that financial analysts suffering a higher level of COVID have a greater likelihood of 14.61% of issuing a pessimistic forecast. From columns

(2) to (4), I add the analyst and year-fixed effects, and the results remain statistically significant at the 1% level.

For the other control variables, I notice that *Firm_Exp* and *Forecast_Age* are significantly negative at the 1% level, suggesting that higher firm experience and a longer forecast horizon would likely reduce the chance of being pessimistic on average. This result is consistent with previous research, such as Cowen et al. (2006) and Bourveau and Law (2021). Some other control variables, though statistically significant, have inconsistent coefficient signs and thus cannot be interpreted. I do not find evidence that working for a top contributor or being a male significantly impacts pessimism. The results in probit and logit models also indicate consistent findings.

[Insert Table 5 here]

3.4.2. COVID severity level and forecast timeliness

I now test hypothesis 2b with *Timeliness* as the dependent variable. Specifically, I examine whether analysts issue less timely forecasts as the COVID severity within their state exacerbates. The results of this regression are reported in Table 6.

Across all four columns, the estimate of *HiCOVID* remains negative and statistically significant at 1% and 10% levels. The regression results suggest that analysts affected by a higher level of COVID are less timely in issuing forecasts after the announcement date than other analysts covering the same firm in the same forecast period. The finding remains significant at 1% level when adding year-fixed effect but becomes less significant with the analyst fixed effect.

[Insert Table 6 here]

Overall, the findings regarding forecast pessimism and forecast timeliness support my first and second hypotheses and align with previous studies, showing that analysts become more pessimistic and slower in issuing forecasts when the COVID level is higher.

3.4.3. COVID severity level and forecast accuracy and frequency

I now test the last hypothesis of my main study, i.e. whether forecast accuracy and frequency are moderated by COVID severity level. For forecast accuracy, regression outputs are reported in table 7.

[Insert Table 7 here]

The results of the PMAFE regressions for the 2019-2020 period validate my hypothesis. The coefficients of *HiCOVID* across all columns in Table 7 are statistically significant and negative, demonstrating that analysts release relatively more accurate forecasts than the average analysts when experiencing a higher COVID severity. This finding is consistent with Cuculiza et al. (2021), who argue that the increase in forecast accuracy is probably due to analysts issuing bold downward forecasts, making them closer to the actual value.

It is also evident in Table 7 that *Forecast_Age* is significantly positive, implying that the earnings forecasts are more accurate as the forecast age gets smaller, similar to many prior findings (Clement and Tse, 2005; Bourveau and Law, 2021; Cuculiza et al., 2021). Likewise, *GExp* is significantly negative across all models, implying that analysts with more experience are associated with greater accuracy. This result should be expected because as an analyst becomes more experienced, she will gain more expertise and make fewer errors.

Surprisingly, estimates of *Firm_Exp* are all statistically significant and positive at the 1% level, suggesting that higher firm experience is associated with lower forecast accuracy, similar to Cuculiza et al. (2021) but contrary to Clement (1999). One possible explanation for this is the concurrent influence of overconfidence bias, which refers to when one overestimates their ability (Kafayat 2014), and anchoring bias, which is when one fails to weigh new information correctly (Campell and Sharpe 2009). These two cognitive factors suggest that as analysts get more familiar with covering a specific firm, they may get too confident in their knowledge of the firm and hence fail to reflect new information appropriately.

Lastly, I examine whether the COVID level impacts the number of forecasts issued by an analyst. The results are presented in Table 8. In contrast to previous sections, I find no difference in the impact of high COVID severity on forecast frequency relative to the low level. Specifically, the estimates of the variable *quar_HiCOVID* are inconsistent and insignificant in the first two columns, indicating that the COVID severity level does not moderate the number of forecasts issued by analysts in a quarter.

[Insert Table 8 here]

Collectively, my empirical findings across the four criteria of earning forecasts indicate that COVID severity levels indeed moderate analysts' performance. Specifically, when COVID severity is higher, even though analysts become more pessimistic, they tend to issue more accurate estimates for the same firm in the same forecasting period. At the same time, it takes more time for analysts to issue forecasts after the earning announcement date. There is, however, no difference in the forecast frequency.

The following chapter presents my final research question, which is another sub-study investigating the impact of WFH on analysts' performance during the Coronavirus pandemic.

4. The impact of WFH on analysts' performance during COVID-19

4.1. Introduction

My previous study documents an effect of COVID-19 on analysts' performance, proxied by four characteristics of forecasts: pessimism, accuracy, timeliness and frequency. It is likely that COVID-19 has psychologically affected analysts, resulting in cognitive biases and altering forecasting activity. However, mental health might not be the only factor that influences financial analysts' performance. One unique consequence of the Coronavirus is that it indirectly forces individuals to telecommute.

During the first wave of COVID-19 in America, stringent lockdowns and social distancing are imposed, temporarily closing many businesses and allowing only essential services to operate. Consequently, in May 2020, the fraction of the workforce teleworking reached its highest peak, around 35.4%, according to the U.S. Bureau of Labor Statistics (2022). Yet, six months into the pandemic, a majority of workers, roughly 71%, with jobs that could be telecommuted were still working from home. More generally, the number of individuals working remotely tripled from 5.7% to 17.9% between 2019 and 2020, as per a survey by the U.S. Bureau of Labor Statistics (2022).

This procedure presents an unprecedented challenge to many workers, as this would be the first time they have to work from home for an unpredictable prolonged period. Consequently, this unusual teleworking movement has again raised questions about employees' performance. Even though a substantial body of literature has been dedicated to understanding this matter, the findings on teleworking's impacts on performance are conflicting.

On the one hand, individuals may be inclined to underperform due to stress from COVID infections, social restrictions, distractions from family, and more interruptions to team collaboration or firms' resources. This notion is directly supported by the theory of "employee engagement", asserting that workers are less engaged in their job if they feel lacking psychological safety and meaningfulness (Kahn 1990). On the other hand, teleworking enables people to spend less time commuting and preparing to get to work. More importantly, it offers more autonomy and flexibility, allowing people to craft the most comfortable working environment, potentially reducing job exhaustion and boosting productivity (e.g. Tietze and Nadin 2011, Sardeshmukh et al. 2012). Consequently, the potential upsides and downsides of WFH during the COVID leave us with an empirical question: whether individuals perform better or worse throughout this unprecedented time, taking into account the influence of WFH.

Considering that financial analyst is not an essential job and can be done from home, I assume that analysts have to telecommute as per the state's policy. I believe this assumption is reasonable, as many large brokerage houses announced allowing WFH during the pandemic's peak, like Charles Schwab (Massa and Gittelsohn 2020), JPMorgan, Citi (Reuters 2021), etc. In light of this, I construct another sub-study to explore the impact of WFH, alongside COVID-19, on analysts' performance, proxied by forecast pessimism, accuracy, timeliness and frequency. The regressions are based on model 4, to which the dummy variable *WFH* is added. The *WFH* variable is equal to 1 if a forecast is issued on the day the WFH policy in that state where the analyst is working is in effect and 0 otherwise. Under this method, I will also test the interaction effect between COVID severity level and WFH, if any, on analysts' performance.

Regression outputs are reported in Table 9 to Table 12. Even though I find that there is an additive and interaction effect on *Pessimism* resulting from WFH, I see no statistically or economically significant effects on the remaining characteristics. This finding suggests that the transition to WFH during the pandemic does not influence financial analysts, probably because they are highly educated and skilled, thus able to adapt to new changes quickly.

4.2. Literature review and hypothesis development

The academic's interest in understanding the implications of WFH is undoubtedly immense. Unfortunately, even with numerous research papers dedicated to exploring its impact on productivity, the literature on this topic remains divided into two opposing views, and the results are far from conclusive.

First, one perspective generally argues that WFH allows for greater autonomy and control over time, and better work-life balance, resulting in better mental health and, in turn, the productivity of employees. For example, Tietze and Nadin (2011) and Sardeshmukh et al. (2012) find an association between working from home (WFH) and less time pressure and greater autonomy, resulting in less job exhaustion. Meanwhile, Ford and Butts (1991) and Lupu (2017) assert that increased autonomy and flexibility are two critical factors that lead to job satisfaction, implying that WFH will lead to higher efficiency. Their deductions are directly supported by findings in psychology literature, which document a positive relationship between mental well-being and productivity. For example, Bubonya, Cobb-Clark and Wooden (2017) highlight the importance of mental health on job performance as they find a 5% increase in absence rates among employees who reported being in a poor state of mind. Similarly, Burton et al. (2004) claim that presenteeism, i.e. attending work but being ineffective, is strongly linked to depression, anxiety, and health status.

Prior to the pandemic, a leading paper in this vein of literature is the one by Bloom et al. (2014), who constructed a randomized experiment in a Chinese company of 16,000 workers over two years. They find a 13% increase in workers' performance from WFH, of which about 4% was from higher productivity per minute, and the remaining 9% was from individuals working longer during their shift period. Likewise, after analyzing patent examiners participating in a work-from-anywhere (WFA) program, Choudhury et al. (2020) find a 4.4%

increase in their work output, inferring that granting employees greater autonomy may improve productivity.

Under the COVID-19 context, while Emanuel and Harrington (2020) discover a 7.5% increase in hourly productivity when a Fortune 500 company employees switched to remote work, Zhang, Gerlowski, and Acs (2022) find that small businesses performed better in states with higher WFH rates. The increase in productivity is also widely cited across many papers, yet they are mostly self-reported. For example, Barrero et al. (2021) indicate that most respondents in a survey of more than 30,000 Americans reported a productivity increase when they had to WFH during the pandemic, while another online survey by Guler et al. (2021) spanning two months also record a similar finding.

In contrast, another strand of literature provides opposing evidence on the effects of WFH on productivity. Papers in this vein generally argue that reducing physical distance between co-workers decreases knowledge-sharing and the effectiveness of collaboration. In addition, home environments and family distractions could deteriorate work output when telecommuting (e.g. Gajendran and Harrison 2007, DeGray 2012, Sutherland 2015). Battiston et al. (2017) support this notion by providing evidence of a causal relation between proximity and performance. Specifically, they observe that productivity increases when coworkers are in the same room. The effect will be even more significant when tasks are more complex and are performed under high pressure, suggesting that telecommuting might be unsuitable when activities are informationally demanding.

In the context of Coronavirus, a recent study by Gibbs et al. (2021) indicates a decrease of 8 – 19% in productivity among 10,000 skilled professionals at an Asian IT services firm. Another study by Aczel et al. (2021) points out that nearly half (47%) of 704 surveyed respondents experienced decreased work efficiency, while 30% experienced no difference when WFH during the outbreak. Likewise, Morikawa (2021), using a survey of more than 3,000 employees in Japan, reveals that work productivity when working from home is only around 60-70% relative to usual business offices. This effect is likely more manifested if firms and employees practised WFH for the first time. The "employee engagement" theory developed by Kahn (1990) consolidates these findings, as it asserts that the more psychological meaningfulness and safety are present, the more engaged the employees are to work.

Accordingly, the results on the impact of WFH on productivity are still far from conclusive. Generally, prior to the pandemic, switching to remote working seems to have the potential to negatively and positively affect productivity. Nevertheless, understanding the implications of WFH during the pandemic becomes even more complex since employees are influenced not only by the telecommuting movement but also by the COVID severity. On the one hand, any positive effects of WFH on mental health may be cancelled out by the impact of COVID-19, resulting in no difference or minor changes in productivity. Alternatively, if there are negative effects, they will be amplified by the progress of the Coronavirus, leading to significant drops in performance. In light of this, I express my final hypothesis in the null form:

Hypothesis 4: WFH does not affect analysts' performance during COVID-19.

4.3. Data and methodology

The sample data remains the same as in previous studies. However, for this research question, I add another dummy variable, *WFH*, to model 4. *WFH* is a dummy variable, which equals one if a forecast is issued on the day stay-at-home (SAH) orders are in effect in the state the analyst is working and zero otherwise. Data on SAH orders are extracted from Oxford COVID-19 Government Response Tracker, a project undertaken by Hale et al. (2021). The project tracks and collects systematic information on policy measures, providing a comprehensive database of policy responses in over 180 countries covering 23 indicators (e.g. school closures, vaccination policy, mandatory masks etc.). Using this database, I can identify the time and the level of a SAH order imposed by the state governments in the U.S.

According to Hale et al. (2021), the project classifies SAH orders into three levels. Level 0 means that no measures were taken. Level 1 indicates "not recommended leaving the house". Finally, Level 2 requires "not leaving the house with exceptions for daily exercise, grocery shopping, and essential trips". In this sub-study, I will only count an analyst working from home when the SAH order in that state is at level 2 – the highest level. Suppose an analyst issues a forecast on the first day their state imposes a "level 3" SAH order, I will deem that forecast is issued when the analyst is working at home.

All other specifications remain the same as in the main study. As a proxy to capture analysts' performance, the independent variables are the earning forecasts' characteristics: pessimism, accuracy, timeliness and frequency. I now repeat all the steps taken in the main study using the following OLS model:

$$Forecast\ properties_{i,j,t} = \alpha + \beta_1 HiCOVID + \beta_2 WFH + \beta_2 HiCOVID^{*}WFH + Controls + FEs \tag{5}$$

where *i, j,* and *t* denote analysts, firms, and quarters, respectively. The dependent variable is the *Forecast properties*, the placeholder for pessimism, accuracy, timeliness and frequency. The measuring methods for most variables in this model remain the same as in the main study (chapter 3).

A key difference is the appearance of *WFH* – the variable of interest in this sub-study. In addition, as the WFH progresses along with the onset of COVID-19, I add an interaction term, *HiCOVID*WFH*, representing the interaction effect between high COVID severity level and

WFH. Including the *WFH* variable and the interaction term allows for exploring the additive and interaction effect, if any, of WFH on the original model.

Another special consideration is the regressions of frequency on the *WFH* variable. Forecast frequency is counted as the number of forecasts issued by an analyst in a quarter, while SAH orders are typically not imposed for the whole quarter but only for a short period. As a result, there is a mismatch in time units, thus requiring adjustments to the model. Particularly, I remove the dummy *WFH* variable and set a new continuous independent one, *days_WFH*, measuring the total number of days the highest-level SAH orders are imposed in each fiscal quarter in each state. For the dependent variable, I use *quar_HiCOVID*, a dummy variable equal to one if the average COVID severity level in that quarter is high. Similarly, for other continuous control variables, I take their averages in that quarter, except for *Firm_Exp*, which is left out in regressions on forecast frequency as it is irrelevant.

4.4. Empirical results

4.4.1. The impact of WFH during COVID-19 on pessimism

I now utilise OLS regressions again to seek answers for my final research question, i.e. WFH has no effects on analysts' forecasting activity during COVID-19. First, I examine its impact on pessimism among analysts. Table 9 presents the empirical regression outputs, with *Pessimism* being the dependent variable.

[Insert Table 9 here]

The regression results show that other control variables remain consistent with previous findings in the main study. *Firm_Exp* and *Forecast_Age* remain significantly negative, implying that higher firm-specific experience and longer forecast horizons would likely reduce the possibility of being pessimistic. This finding seems reasonable because the more experience in a firm and the more time an analyst takes to issue an estimate, the more likely they are to adapt to any shocks occurring in the market. Other variables remain insignificant or not interpretable.

Nevertheless, the results on the variables of interest are pretty interesting. The coefficients of *HiCOVID*, *WFH*, and *HiCOVID*WFH*, are all statistically significant at 1% level. However, although the signs of *HiCOVID* and *WFH* estimates are both negative - consistent with previous findings, the interaction term between high COVID level and WFH turns out positive. The same observations can be made across all tests with control variables and fixed effects.

Technically, ceteris paribus, the model predicts that the effect of COVID severity level increasing from low to high, depending on whether analysts are working from home, on pessimism is *0.1283 - 0.1392*WFH*. So for states with no SAH orders imposed (*WFH = 0*), the estimated effect is an increase of 12.83% in analysts generating issuing pessimistic forecasts, while for states with SAH orders in place (*WFH = 1*), the predicted increase in pessimism amounts to *0.1283 - 0.1392*1 = - 0.0109*. This negative value indeed suggests a potential decrease in pessimism, implying the WFH effect outweighs COVID severity for all WFH observations in the data.

I propose one simple explanation for this occurrence. It is likely that as the impact of COVID is too immense and unexpected, analysts tend to prefer to work from home, where they may feel closer to family and safer. Consequently, when the COVID severity increases to a high level, telecommuting analysts will feel more positive than those still working in offices. Even though the model indicates the increase in severity level still results in more pessimism overall, that effect can be mitigated if analysts are allowed to work from home.

In the next section, I will present regression results collectively on the remaining characteristics of earning forecasts: accuracy, timeliness, and frequency.

4.4.2. *The impact of WFH during COVID-19 on analysts' accuracy*

I test the same regression model on analysts' accuracy to examine the effect of WFH and COVID severity on analysts' accuracy. Table 10 presents the empirical regression outputs, with *PMAFE* being the dependent variable.

[Insert Table 10 here]

Regarding control variables, *GExp* is essential in determining analysts' accuracy, as its coefficients are significantly negative across all tests. The output indicates that the more experienced analysts are, the more precise their estimates. The coefficients of *Forecast_Age* are all significantly positive, implying that the longer it takes for analysts to produce a forecast, the less accurate it is. These findings are consistent with many prior studies, like Clement (1999) or Cuculiza (2021).

Noticeably, across all empirical tests, the estimates of *HiCOVID* and the interaction term *HiCOVID*WFH* remain statistically significant, although they have opposite signs. This result implies that the effect of COVID severity level on forecast accuracy is likely conditional on SAH policies. Specifically, ceteris paribus, without SAH orders being imposed, analysts tend to become more accurate as the COVID severity increases. Yet, when they have to work from home, that effect is almost cancelled out by the telecommuting movement, resulting in practically no difference in accuracy. Interpreting this finding is puzzling and would require further investigation.

4.4.3. *The impact of WFH during COVID-19 on forecast timeliness and frequency*

In this section, I examine the effects of WFH and COVID severity on forecast timeliness and frequency. Tables 11 and 12 present my empirical results, with *Speed* being the dependent variable measuring timeliness and *Frequency* being the predictor variable measuring forecast frequency, respectively.

[Insert Tables 11 and 12 here]

In general, I find no evidence of the impact of WFH on these characteristics of earning forecasts. The estimates of variables of interest in these models are all inconsistent and not interpretable. Yet, this should not be too surprising, as many papers point out that WFH has a minimal effect on highly paid and highly skilled employees (e.g. Morikawa 2021).

Overall, the telecommuting movement during COVID-19 seems to have no real influence on analysts' forecasting activity. Although I see a significant difference in pessimism, its impact on other characteristics of forecasts seems insignificant and not meaningful enough. I suggest further research needs to be done to explore the implications of WFH during the pandemic, as separated from COVID-19's influence.

5. Robustness Tests

This chapter presents robustness tests on my parent study, i.e. to which extent the COVID severity moderates analysts' forecasting activity. I will focus on testing the two most critical characteristics of earning forecasts, i.e. pessimism and accuracy, which are also the most commonly studied in the extant literature.

5.1. Pessimism or Firms' Exposure to COVID-19?

A potential concern with my findings is that analysts' pessimism may be due to fundamental causes, not psychological effects. Hassan et al. (2021) find a substantial variation in stock returns around firms' earning calls during the pandemic, implying a negative valuation effect for companies with greater exposure to COVID-19[2]. Therefore, there is a possibility that analysts become less optimistic in forecasting simply because firms are being increasingly exposed to the pandemic, not because they are psychologically affected by it.

Drawing on the research by Hassan et al. (2021), I include another control variable, *Firm_Exposure*, to control for the possible fundamental effects of COVID-19 on analysts' earning forecasts. I use the same definition and data set provided by Hasan et al. (2021)[3], and merge it with my data. Regressions' results presented in table 13 indicate that the *Firm_Exposure* variable is statistically significant across all tests, implying an association between firms' exposure to COVID-19 and analysts' forecasts. This result further consolidates Hassan et al.'s findings and highlights another channel through which COVID-19 exposure can damage business outlook.

[Insert Table 13 here]

Noticeably, after controlling for the COVID-19 exposure, my main variable of interest, *HiCOVID*, remains statistically significant, indicating that financial analysts are indeed psychologically affected by the pandemic since they become more pessimistic as the COVID-19 severity exacerbates at the state level.

[2] According to Hassan et al. (2021), COVID-19 exposure is quantified generally by counting and categorizing the number of times the disease (and its synonyms) is mentioned in the quarterly earnings conference calls.
[3] Data on firm-level exposure to COVID-19 by Hassan et al. (2021) can be accessed through: firmlevelrisk.com

5.2. Excluding analysts residing in New York state

Notably, most analysts in the sample reside in New York state, accounting for approximately 76% of all analysts in both years 2019 and 2020, as shown in Figure 3B. I now exclude these individuals from my models to test whether these analysts drive the outcomes. The new results are reported in Table 14. Even though the data sample drops dramatically from 401,427 observations to 101,037 observations after the exclusion, the results indicate no difference in the variable of interest *HiCOVID*, besides the increase in economic significance. This finding suggests that my empirical results are not driven by analysts concentrating in New York state.

[Insert Table 14 here]

5.2. Including only analysts who appear in both years

I also observe that 61 financial analysts exit the data sample after 2019, and 92 new persons enter during 2020. Even though these numbers are relatively small to the whole sample (around 10%), there is still a possibility that these analysts somewhat drive my results. To address this concern, I re-estimate my models and include only analysts who appear in both 2019 and 2020. The data sample drops slightly from 401,427 to 376,945 observations. Results are presented in Table 15. Again, the variable of interest appears statistically significant, confirming that the exited and new analysts in the sample data over the two years do not drive the results.

[Insert Table 15 here]

5.3. Excluding forecasts made around severe weather events and terrorism

Recent studies by Dehaan et al. (2017) and Bourveau and Law (2021) show that weather can induce pessimism and affect forecast accuracy. Meanwhile, Cuculiza et al. (2021) prove that terrorism could cause a similar effect. Therefore, I decide to remove observations around severe weather events and terrorism to ensure that my findings are distinct from the impact of weather and terrorism.

I collect extreme weather events from the National Oceanic and Atmospheric Administration website for 2019-2020. I define a weather event as severe if the property damage caused by that event is greater than $1 million. Following Dehaan et al. (2017), any forecasts made within three days of the event by analysts living in the affected state will be excluded. For terrorism, I collect data from the Global Terrorism Database (GTD) and remove all forecasts made within 30 days by analysts living in the same area, following Cuculiza et al. (2021). The number of observations in my data sample falls to 290,706 after the change. The empirical results in Table 16 show consistent findings with my previous regressions.

[Insert Table 16 here]

5.4. Placebo test

Another possible concern is that all effects I capture among analysts during the pandemic are a mere coincidence. Therefore, I employ a placebo test to capture the impact of the COVID risk level on analysts' sentiment and forecast accuracy. Specifically, I randomize the COVID levels for every analyst-firm observation and re-estimate my regressions over ten times. If my findings are genuinely a coincidence that I happen to capture during the pandemic, the variable of interest, *HiCOVID,* should remain statistically significant. As shown in Table 17, the regression output aligns with my expectation, that is, the key variable is no longer meaningful. This evidence eliminates the possibility that my research merely captures a coincident trend in previous regressions.

[Insert Table 17 here]

5.5. Firms' fundamentals

In this section, I examine the possibility of analysts' estimates driven by firms' characteristics. Generally speaking, it is potentially likely that analysts issue more optimistic forecasts for larger, more profitable firms while negative ones on small, illiquid stocks. As a result, I account for certain firms' fundamentals in regressions on *Pessimism* and *PMAFE* and test the models again. Following previous studies, I include commonly studied firms' characteristics such as market value, size, profitability, ln(Turnover), and stock price. Results are reported in Table 18.

[Insert Table 18 here]

Table 18 shows that even though some of the firms' fundamentals are statistically significant while the key variables become less significant, it is still evident that COVID severity levels affect analysts' pessimism and accuracy. The results suggest that my findings are insensitive to the added control variables, specifically firms' fundamentals.

6. Conclusion

6.1. Summary of main findings and contributions

In this thesis, I present two sub-studies along with one primary research. The first sub-study investigates whether there is any difference in analysts' sentiment and accuracy in post-pandemic relative to pre-pandemic, motivated by the extensive papers in psychology and analyst literature. Consistent with prior findings, my results suggest that the Coronavirus pandemic, as an exogenous shock, negatively impacts analysts' sentiment, resulting in more pessimistic forecasts. However, quite interestingly, its consequence is not always negative, as analysts' accuracy improves during the onset of the pandemic.

The next chapter presents my focus research which is contingent on the first sub-study. Specifically, I investigate how COVID severity levels moderate analysts' performance, motivated by the 'affect heuristic' theoretical framework. I find that higher COVID severity results in higher pessimism among analysts and, simultaneously, more accurate forecasts, relative to the low severity level. Yet, they become less timely and indifferent in the number of forecasts issued each quarter. I argue two possible reasons for this occurrence.

First, there is likely a trade-off between accuracy and timeliness. The Coronavirus is genuinely unprecedented and unexpected in many aspects. As a result, during the onset of the pandemic, analysts face a great amount of uncertainty, leading them to take more time to issue forecasts. In return, they will have more time to reflect on new information and adjust accordingly, thus increasing forecast accuracy. Secondly, it's been widely cited that analysts' overoptimism is linked to higher forecast errors. Therefore, since it's found that a more severe COVID level prompts higher pessimism, it is possible that the optimism among analysts is being corrected, resulting in better accuracy.

Finally, in my last sub-study, I examine whether the WFH and COVID severity influence analysts' forecasting activity. While I document a significant difference in pessimism, its impact on other characteristics of earning forecasts seems insignificant and not meaningful enough. As a result, I conclude that WFH during COVID-19 has no real influence on analysts' performance.

My findings contribute to a range of literature. First, it adds to the analyst literature by examining the effect of an exogenous adverse event, while previous studies show only the overall impact. Given that the COVID pandemic is long-lasting and its severity levels vary over time across different locations, it is essential to understand the effect of different severity levels on analysts' performance. In addition, my findings reaffirm the results of many previous studies, especially regarding pessimism and forecast timeliness, i.e. analysts tend to be pessimistic and less timely when experiencing an exogenous shock. Also, my findings of increased forecast accuracy support Cuculiza et al. (2021), who documents a positive association between pessimism and accuracy.

My findings also contribute in several ways to the psychological and behavioural finance literature. I provide firm evidence supporting the affect heuristic, suggesting that individuals may react unequally to different severity levels of an event. My research also complements findings that financial analysts are subject to a range of biases despite being highly skilled professionals, leading them to alter their forecasting activity. This again supports investors' allegations that analysts' decisions may be driven by their incentives and working environment factors, resulting in less reliable estimates.

At the same time, I provide evidence that WFH, alongside the COVID severity, does not significantly influence analysts' outputs. As many prior papers point out, high education can be one factor that facilitates the transition of moving from office to home, resulting in no difference in performance (e.g. Morikawa 2021). This finding has many essential implications in today's world, where WFH is increasingly becoming a global trend.

Lastly, my research also provides some practical implications for the participants of the capital markets, firms and policymakers. Investors will have to assess analysts' forecasts more cautiously, questioning the investment value from their estimates. Also, firms and policymakers should adopt appropriate policies to support employees in distress or having difficulties after experiencing an adverse event. Dealing with cognitive biases is more challenging than regulating conflicts of interest; hence, it is a question that brokerage houses and regulators may have to examine.

6.2. Limitations and directions for future research

One common limitation of using the IBES database for earning forecasts is that analysts have the autonomy to provide or choose to disclose any of their estimates, making the data prone to selection bias. In addition, locating analysts' states by looking at their office phone numbers in Refinitive's reports may lead to errors. It is possible that the residing state is different from where they work or that analysts switch to another office but not yet update their contact details.

Also, I couldn't determine whether pessimism among analysts results from COVID-19 or a trend pre-existing before the pandemic. Similarly, even though I document an increase in pessimism and accuracy, I can't identify whether these two have any association, i.e. whether the pandemic-induced pessimism directly accounts for the increase in forecast accuracy. Lastly, there might be opposing views against how I measure COVID severity, which is based on infected cases per 100,000 inhabitants. Not to mention, each analyst's perception of risk can be very different, and not everyone would constantly update the COVID news. Moreover, using SAH orders may not truly reflect the telecommuting movement. It is possible that even when SAH practices are removed, companies still allow their employees to work from home to mitigate the spread and protect the population's health.

For future research, I recommend examining whether the impact of different COVID severity diminishes over time. In fact, although the pandemic appears as an exogenous shock at first, analysts may grow familiar with and adapt to it as it progresses. As a result, any effect of COVID-19 on analysts' performance may diminish as time goes by, eventually leading to no effect at all. Secondly, along with SAH orders, one may consider studying the impact of other policy responses during the pandemic, such as school closures or mask mandatory policy. Such research will undoubtedly contribute to setting policies in the capital markets and society during challenging times. In addition, I strongly recommend that more sophisticated research should be undertaken to examine the effects of WFH during the pandemic, as this is still a very promising premise. Finally, I recommend investigating the market responses following the change in analysts' performance after experiencing exogenous shocks, i.e. whether markets recognise the impact and react accordingly.

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Appendix I. Variable definitions

Definitions of the variables used in this paper are provided below.

Variable Name	Description	Source
Variable of Interest		
Post_Covid	Indicator variable equal one if a forecast is issued after February 2022.	I/B/E/S
HiCOVID	Indicator variable set to one if a state's level of COVID severity is high on the day a forecast is issued. The level is high when new COVID cases over the 28 days prior to the forecast date are above 100.	US Centres for Disease Control and Prevention
quar_HiCOVID	Indicator variable equal to one if the average COVID severity level in a state in a fiscal quarter is high.	US Centres for Disease Control and Prevention
WFH	Indicator variable equal to one if a forecast is issued on the day a stay-at-home order is in effect (state level).	Oxford Government Response Tracker
days_WFH	Continuous variable measuring how many days in a quarter the highest-level SAH orders are in effect.	Oxford Government Response Tracker
Dependent Variables		
$Pessimism_{i,j,y}$	Indicator variable equal one if an analyst's forecast is less than the latest consensus forecast for the same firm and the same forecasting period.	I/B/E/S
Speed	Evaluates forecast timeliness. First, each analyst is assigned a rank based on how early they issue forecasts for a firm within the same forecasting period. Then the following equation is used to measure forecast timeliness: $Speed = 100 - \left[\frac{Rank-1}{Number\ of\ analysts-1}\right] \times 100$ A higher Speed value indicates higher forecast timeliness.	I/B/E/S

PMAFE	Proportional Median Absolute Forecast Error measures forecast accuracy, computed as follows: $PMAFE_{i,j,t} = \frac{AFE_{i,j,t} - \overline{AFE_{J,t}}}{\overline{AFE_{J,t}}}$ The absolute forecast error AFE is the difference between an analyst's forecast and the actual EPS. A negative PMAFE indicates an analyst performing better than the average and vice versa.	I/B/E/S
Frequency	The total number of forecasts issued by an analyst in each quarter.	I/B/E/S

Other Variables

GExp	An analyst's general experience - the number of years between a forecast and when an analyst first started a financial job.	LinkedIn, I/B/E/S
Firm_Exp	Firm experience – the number of years since an analyst first covered a firm until the forecast date.	I/B/E/S
Forecast_Age	The number of days between the forecast and earnings announcement date.	I/B/E/S
Porfolio_Firms	The number of firms an analyst is covering in a quarter.	I/B/E/S
Industries_covered	The number of industries an analyst is covering in a quarter.	I/B/E/S, CRSP
Top10 Estimator	Dummy variable set to one if the brokerage house an analyst is working for is in the top 10 of the 2021 All-America Research Team Rankings.	Institutional Investors
Male	Dummy Variable equal one if an analyst is male.	LinkedIn
Market Value	Firms' number of shares mutiplied by stock prices.	CRSP
Size	Natural log of Market Value	CRSP
Profitability	ROA – net income divided by total assets	Compustat
Ln(Turnover)	Natural log of shares volume traded divided by the number of shares.	CRSP
Stock Price	Firm's stock price on market	CRSP

Figures and Tables

Figure 1: 7-day average cases and deaths due to COVID-19 in the U.S. since 2020.

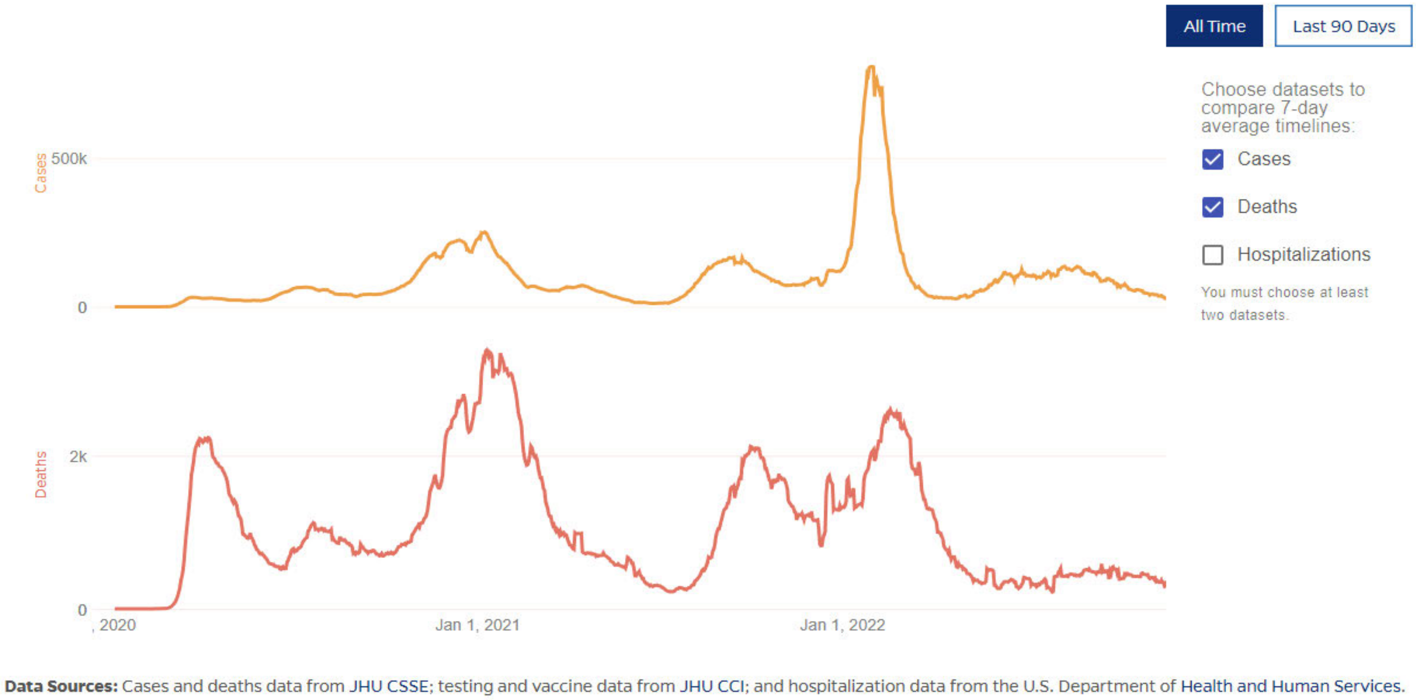

Figure 1 presents timeline data on 7-day average of cases and deaths due to COVID-19 in the United States of America from Jan 2020 to present, showing how significant and persistent the pandemic is. Data is extracted from the databse of Johns Hopkins University: Coronavirus Resource centre. Access via: https://coronavirus.jhu.edu/map html

Figure 2: Proportion of pessimistic forecasts in each quarter between 2019 and 2020.

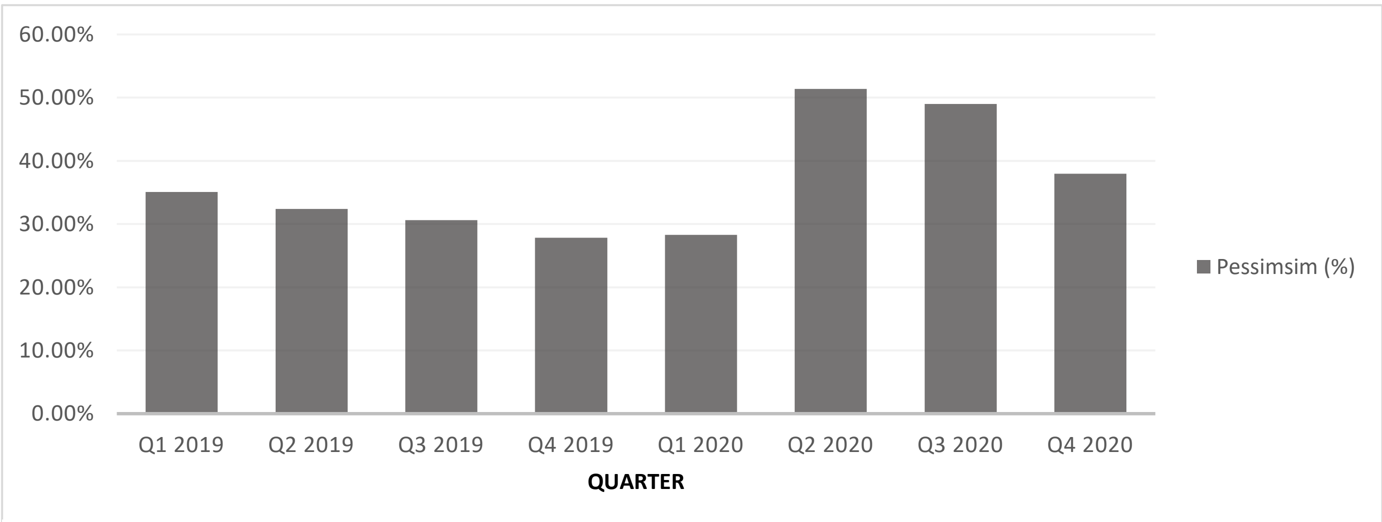

Figure 2 plots the proportion of pessimistic forecasts in each quarter btween 2019 and 2020. Pessimistic forecasts are estimates below consensus forecasts. Earning forecasts data is obtained from IBES Actuals and History.

Figure 3A: COVID-19 Death Rate in the US by State (deaths per 100,000) since 21st Jan 2020

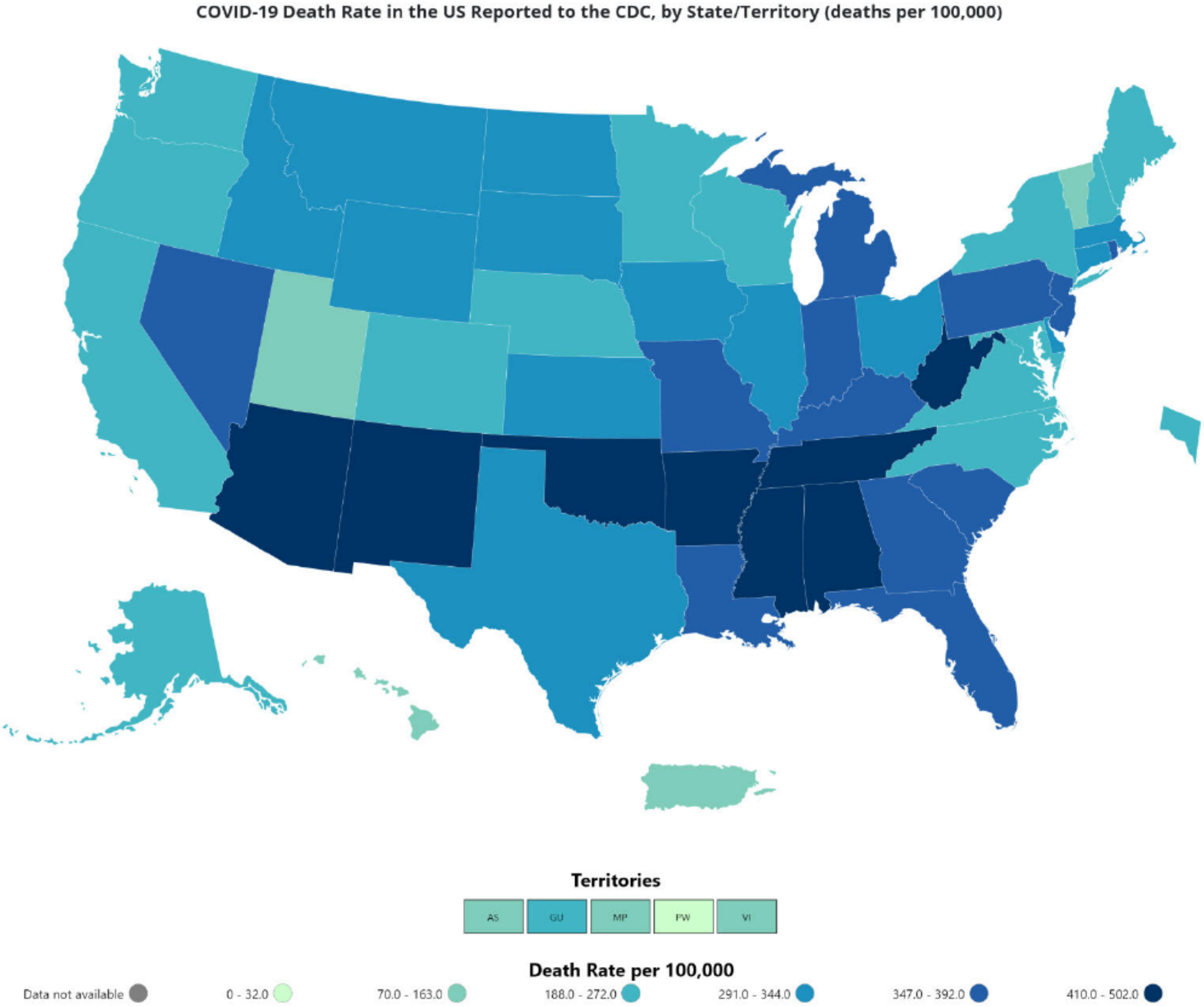

Figure 3A display the COVID death rate per 100,000 across different states since 21st January 2020, indicating the variety of COVID severity levels across different locations and time. The figure is downloaded directly from US CDC website. Access via: https://covid.cdc.gov/COVID-data-tracker/#cases_deathsper100k

Figure 3B: Distribution of earning forecasts across states over the whole period of 2019-2020

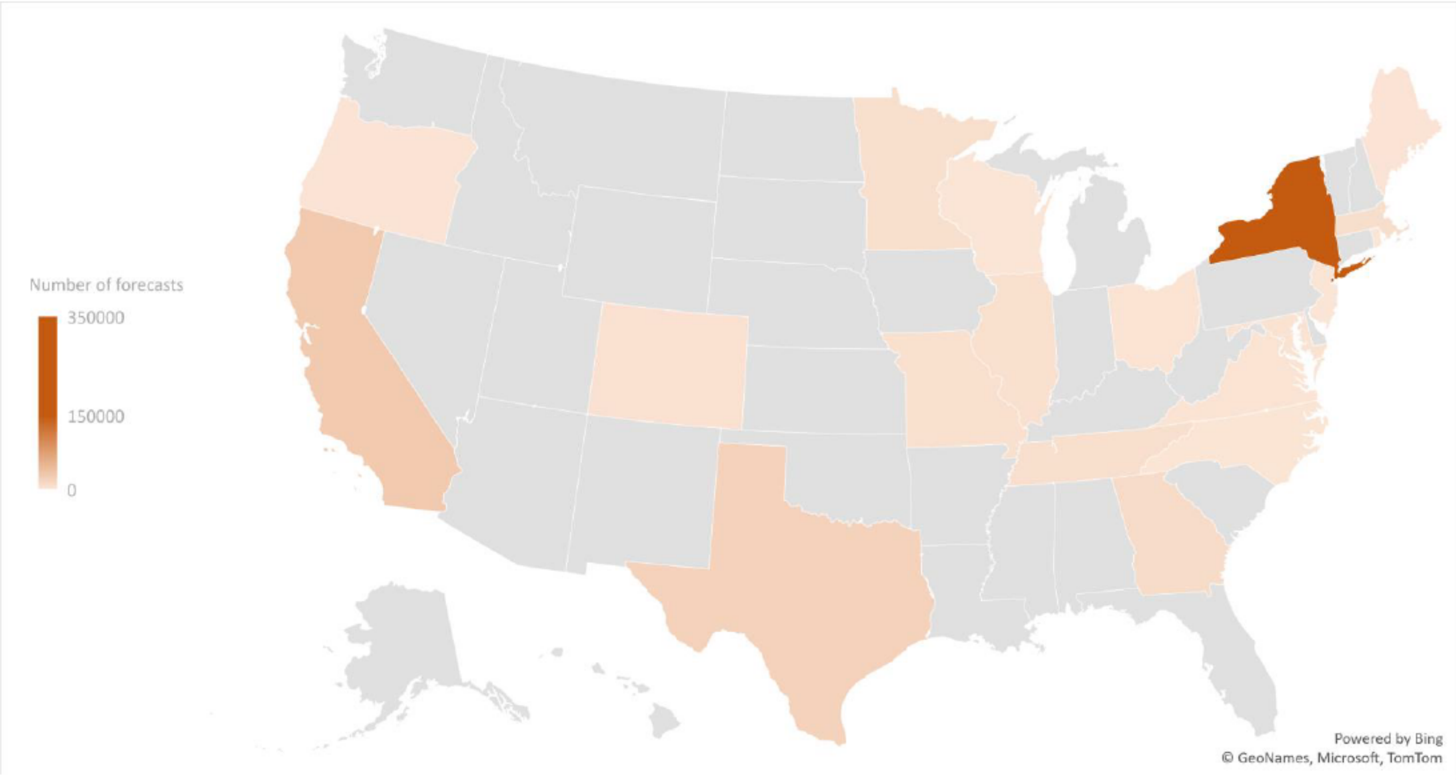

Figure 3B display the distribution of earning forecasts across different states in the final sample of my research. States not in the sample are uncolored. The map is manually generated.

Table 1: Sample Selection Procedure

Data	**Source**	**Observations**	**Analysts**
EPS forecasts and actuals	IBES	996,784	3,398
(after filtered)		650,264	1,268
Analysts' reports	Refinitiv	1,151,158	4,739
(after filtered)		569,177	1,806
Recommendations	IBES	41,215	3,659
Merged file (final data sample)		401,427	771

Table 1 summarises the sample selection procedure. The final sample data is used for all studies of this research. All data are collected for the period 2019-2020.

Table 2: Summary Statistics

Panel A: Summary Statistics

Variables	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Pessimism	401,426	0.39	0.49	0	0	1	1
GExp (years)	401,426	17.61	6.04	2	13	21	47
Firm_Exp (years)	401,328	5.16	5.00	0	1.26	7.63	20.96
Forecast_Age (days)	401,426	186.36	104.15	0	93	273	581
Portfolio_firms	401,426	20.31	8.25	1	15	25	55
Industries_covered	401,426	4.82	2.53	1	3	7	15
Male	401,426	0.90	0.30	0	1	1	1
WFH	401,426	0.59	0.75	0	0	1	2
PMAFE	385,447	1.56	10.62	-1	-0.76	1	1.629
quar_HiCOVID	401,426	0.71	0.85	0	0	1.7	3

Table 2 Panel A presents summary statistics for the variables studied in this research. All variables are defined in Appendix I.

Panel B: Distribution of Analysts and Affected Forecasts								
State	**Number of analysts**		**Number of forecasts affected by each COVID level *(incl. revisions)***					
	Year		US CDC's COVID levels				Re-defined COVID levels	
	2019	*2020*	*Green*	*Orange*	*Red*	*Yellow*	*LOW*	*HIGH*
California	48	52	16417	5568	831	6044	21985	6875
Colorado	3	2	2736	174	188	743	2910	931
Georgia	14	13	5658	1551	1092	1766	7209	2858
Illinois	5	12	2260	1552	589	591	3812	1180
Maine	2	2	534	10	10	495	544	505
Maryland	4	5	1205	617	12	189	1822	201
Massachusetts	12	12	4207	1040	580	1362	5247	1942
Minnesota	12	11	4464	896	423	739	5360	1162
Missouri	12	12	3248	646	568	1057	3894	1625
New Jersey	3	4	95	20	11	28	115	39
New York	518	541	174420	27425	32652	65859	201845	98511
North Carolina	1	1	266	93	5	64	359	69
Ohio	3	3	589	182	70	335	771	405
Oregon	2	3	387	115	52	514	502	566
Rhode Island	1	0	323	0	0	0	323	0
Tennessee	12	11	4051	223	1036	1148	4274	2184
Texas	24	24	13593	1648	2069	2623	15241	4692
Virginia	1	1	728	302	0	191	1030	191
Wisconsin	1	1	143	38	32	34	181	66
Total	*678*	*710*	*235324*	*42100*	*40220*	*83782*	*277424*	*124002*

Panel B reports the distribution of analysts and affected forecasts made under different levels of COVID severity across U.S. states during 2019-2020. According to the US CDC, the COVID severity is categorized into four groups: green if new cases per 100,000 population over the past 28 days are less than 50, yellow if it's between 50-99, orange when between 100-500, and red if above 500. Within the scope of this study, I re-define COVID severity into two categories: LOW if it's green and yellow, and HIGH if it's orange and red based on US CDC's definitions.

Table 3: Correlation Matrix

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
[1] HiCOVID	1									
[2] General Exp	0.03	1								
	(<.001)									
[3] Firm Exp	0.00	0.42	1							
	(-0.02)	*(<.001)*								
[4] Forecast Age	-0.03	0.00	0.00	1						
	(<.001)	*(-0.01)*	*(-0.11)*							
[5] Portfolio: Firms	0.01	0.15	0.09	0.00	1					
	(<.001)	*(<.001)*	*(<.001)*	*(-0.64)*						
[6] Industries_covered	0.02	0.07	0.05	0.01	0.42	1				
	(<.001)	*(<.001)*	*(<.001)*	*(<.001)*	*(<.001)*					
[7] Top10 Estimator	-0.01	-0.05	-0.01	-0.02	-0.03	0.04	1			
	(<.001)	*(<.001)*	*(<.001)*	*(<.001)*	*(<.001)*	*(<.001)*				
[8] Male.	-0.01	0.03	-0.03	0.00	0.08	0.02	-0.09	1		
	(<.001)	*(<.001)*	*(<.001)*	*(-0.26)*	*(<.001)*	*(<.001)*	*(<.001)*			
[9] WFH	0.57	0.02	0.01	-0.01	0.01	0.01	-0.02	-0.01	1	
	(<.001)	*(<.001)*	*(<.001)*	*(<.001)*	*(0.00)*	*(<.001)*	*(<.001)*	*(<.001)*		
[10] quar_HiCOVID	0.71	0.05	0.02	-0.07	0.02	0.03	0.01	0.00	0.45	1
	(<.001)	*(<.001)*	*(<.001)*	*(<.001)*	*(<.001)*	*(<.001)*	*(<.001)*	*(-0.22)*	*(<.001)*	

Table 3 presents Pearson correlation coefficients between variables studied in this research. P-values are reported in parentheses. All variables are defined in Appendix I.

Table 4: The Overall Effect of COVID-19 on Pessimism and Accuracy

	Pessimism				PMAFE	
	OLS		Probit	Logit	OLS	
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Covid	0.2005***	0.2812***	0.5290***	0.8528***	-0.9884***	-1.2941***
	(0.0015)	(0.0027)	(0.0041)	(0.0066)	(0.0343)	(0.0625)
GExp	-0.0007***	-0.0800***	-0.0018***	-0.0030***	-0.0230***	0.3704***
	(0.0001)	(0.0025)	(0.0004)	(0.0006)	(0.0031)	(0.0574)
Firm_Exp	-0.0007***	-0.0009***	-0.0020***	-0.0030***	0.0190***	0.0145***
	(0.0002)	(0.0002)	(0.0004)	(0.0007)	(0.0038)	(0.0046)
Forecast_Age	-0.0003***	-0.0003***	-0.0009***	-0.0014***	0.0075***	0.0080***
	(0.00001)	(0.00001)	(0.00002)	(0.00003)	(0.0002)	(0.0002)
Porfolio_Firms	-0.0047***	0.0086***	-0.0129***	-0.0206***	-0.0060***	0.0406***
	(0.0003)	(0.0015)	(0.0009)	(0.0014)	(0.0023)	(0.0080)
Industries_covered	-0.0046***	0.0092***	-0.0047***	0.0085***	-0.0121***	-0.0195***
	(0.00)	(0.00)	(0.00)	(0.00)	0.0427***	-0.1444***
Top10 Estimator	0.0073***	-0.0385***	0.0199***	0.0320***	0.2490***	0.2198
	(0.0016)	(0.0097)	(0.0044)	(0.0071)	(0.0365)	(0.2222)
Male	0.0036	1.8154***	0.0099	0.0163	0.1869***	-6.3976
	(0.0025)	(0.2771)	(0.0068)	(0.0111)	(0.0568)	(6.2047)
Constant	0.3607***	0.9838***	-0.3591***	-0.5829***	0.5047***	-4.5454
	(0.0041)	(0.2718)	(0.0111)	(0.0180)	(0.0926)	(6.0809)
Analyst F.E.	No	Yes	No	No	No	Yes
Year F.E.						
Observations	401,328	401,328	401,328	401,328	385,355	385,355
R2	0.0485	0.0803			0.0084	0.0270
Adjusted R2	0.0484	0.0785			0.0084	0.0251

Table 4 reports the regression output of Pessimism and PMAFE on the *Post_Covid* variable, examining whether analysts' sentiment and accuracy are altered during post-pandemic. All variables are defined in Appendix I. The dependent dummy variable, Pessimism, equals one if an analyst's EPS forecast is lower than the consensus and 0 otherwise. A negative PMAFE indicates higher accuracy relative to their peers. All columns estimate the model with control variables, with 2nd and 6th columns including fixed effects, and the last columns (3) and (4) using probit and logit regressions. Robust standard errors are reported in parentheses. Subscripts ***,**,* indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Regressions on Pessimism for period 2019-2020

	Pessimism					
	OLS				Probit	Logit
	(1)	(2)	(3)	(4)	(5)	(6)
HiCOVID	0.1461***	0.1105***	0.0917***	0.0907***	0.3754***	0.6026***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
GExp	-0.0001	0.0629***	-0.0004***	0.0272***	-0.0001	-0.0002
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Firm_Exp	-0.0008***	-0.0006***	-0.0008***	-0.0008***	-0.0021***	-0.0033***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Forecast_Age	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0009***	-0.0015***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Porfolio_Firms	0.0015***	-0.0007**	0.0015***	-0.0011***	0.0041***	0.0066***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Industries_covered	-0.0046***	0.0092***	-0.0047***	0.0085***	-0.0121***	-0.0195***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Top10 Estimator	0.0092***	-0.0228**	0.0083***	-0.0405***	0.0243***	0.0393***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)
Male	0.0048*	-1.3860***	0.0044*	-0.5823**	0.0131*	0.0206*
	(0.0000)	(0.2800)	(0.0000)	(0.2800)	(0.0001)	(0.0001)
Constant	0.4125***	-0.4082	0.1188	-0.3459	-0.2212***	-0.3531***
	(0.0000)	(0.2700)	(0.4800)	(0.5005)	(0.0001)	(0.0002)
Analyst F.E.	No	Yes	No	Yes	No	No
Year F.E.	No	No	Yes	Yes	No	No
Observations	401,328	401,328	401,328	401,328	401,328	401,328
R2	0.0215	0.0569	0.0292	0.0595		
Adjusted R2	0.0215	0.0551	0.0292	0.0577		

Table 5 reports the regression output of *Pessimism* on high COVID level and other control variables, i.e. whether the higher level of COVID severity causes higher pessimism in analysts' forecasts compared to the consensus. All variables are defined in Appendix I. The dependent dummy variable, Pessimism, equals one if an analyst's EPS forecast is lower than the consensus and 0 otherwise. All columns estimate the model with control variables, with 2nd to 4th columns including fixed effects, and the last two columns using logit and probit regressions. Robust standard errors are reported in parentheses. Subscripts ***,**,* indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Regressions on Forecast timeliness for the period 2019-2020

	SPEED			
	OLS			
	(1)	(2)	(3)	(4)
HiCOVID	-3.3558***	-0.8684*	-1.7970***	-1.0027*
	(0.5000)	(0.5002)	(0.5500)	(0.5300)
GExp	-0.039	-2.6087***	-0.0326	-2.8596***
	(0.0300)	(0.2500)	(0.0300)	(0.3004)
Firm_Exp	0.1266***	0.0067	0.1210***	0.0057
	(0.0300)	(0.0400)	(0.0300)	(0.0400)
Forecast_Age	0.0363***	0.0350***	0.0381***	0.0350***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Porfolio_Firms	0.0285	-0.0369	0.0305	-0.0407
	(0.0200)	(0.0600)	(0.0200)	(0.0600)
Industries_covered	-0.2911***	1.4048***	-0.3033***	1.4017***
	(0.0600)	(0.2600)	(0.0600)	(0.2600)
Top10 Estimator	2.3875***	-8.0454***	2.3913***	-8.1510***
	(0.3000)	(2.5001)	(0.3000)	(2.5100)
Male	-2.3105***	49.4101***	-2.3700***	53.2725***
	(0.4008)	(17.1600)	(0.4800)	(17.5100)
Constant	54.9121***	83.3586***	55.1006***	87.6752***
	(0.7700)	(17.0004)	(0.7007)	(17.4800)
Analyst F.E.	No	Yes	No	Yes
Year F.E.	No	No	Yes	Yes
Observations	75,396	75,396	75,396	75,396
R2	0.0126	0.1383	0.0132	0.1383
Adjusted R2	0.0125	0.1296	0.0131	0.1296

Table 6 reports the regression output of SPEED on high COVID level and other control variables, i.e. whether the higher level of COVID severity causes analysts to be slower in issuing forecasts after the announcement date. All variables are defined in Appendix I. A higher value of SPEED indicates better timeliness. All columns estimate the model with control variables, while the last three measure different fixed effects. Robust standard errors are reported in parentheses. Subscripts ***,**,* indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Regressions on PMAFE for the period 2019-2020

	PMAFE			
	OLS			
	(1)	(2)	(3)	(4)
HiCOVID	-0.7669***	-0.4883***	-0.6774***	-0.5724***
	(0.0400)	(0.0500)	(0.0500)	(0.0500)
GExp	-0.0269***	-0.3540***	-0.0264***	-0.5068***
	(0.0000)	(0.0300)	(0.0000)	(0.0400)
Firm_Exp	0.0197***	0.0139***	0.0197***	0.0129***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Forecast_Age	0.0077***	0.0081***	0.0077***	0.0081***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Porfolio_Firms	-0.0063***	0.0387***	-0.0062***	0.0371***
	(0.0000)	(0.0100)	(0.0000)	(0.0100)
Industries_covered	0.0420***	-0.1427***	0.0422***	-0.1458***
	(0.0100)	(0.0300)	(0.0100)	(0.0300)
Top10 Estimator	0.2353***	0.1856	0.2367***	0.1072
	(0.0400)	(0.2002)	(0.0400)	(0.2200)
Male	0.1762***	9.7109	0.1768***	13.1554**
	(0.0600)	(6.1001)	(0.0600)	(6.1300)
Constant	0.2599***	2.5293	-3.5268	0.2844
	(0.0900)	(6.0600)	(10.5007)	(12.1100)
Analyst F.E.	No	Yes	No	Yes
Year F.E.	No	No	Yes	Yes
Observations	385,355	385,355	385,355	385,355
R2	0.0056	0.0235	0.0089	0.0267
Adjusted R2	0.0056	0.0216	0.0088	0.0247

Table 7 reports the regression output of PMAFE on high COVID level and other control variables, i.e. whether the higher level of COVID severity would impact the accuracy of analysts' earning forecast. All variables are defined in Appendix I. A lower value of PMAFE indicates higher forecast accuracy. All columns estimate the model with control variables, while the last three measure different fixed effects. Robust standard errors are reported in parentheses. Subscripts ***,**,* indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Regressions on Forecast Frequency for the period 2019-2020

	Forecast Frequency			
	OLS			
	(1)	(2)	(3)	(4)
quar_HiCOVID	1.3887	-0.8467	-10.3710***	-4.0414***
	(1.3345)	(1.1588)	(1.5837)	(1.1055)
GExp	-0.0950***	0.9797***	-0.0996***	-6.7999***
	(0.0263)	(0.2501)	(0.0259)	(0.3787)
Firm_Exp				
Forecast_Age	0.2222***	0.2988***	0.2373***	0.1933***
	(0.0173)	(0.0181)	(0.0171)	(0.0177)
Porfolio_Firms	5.2633***	4.5963***	5.2592***	4.6135***
	(0.0818)	(0.1829)	(0.0808)	(0.1735)
Industries_covered	0.9695***	-0.6176	0.9842***	-0.6239
	(0.2908)	(0.7396)	(0.2871)	(0.7014)
Top10 Estimator	2.3839*	4.0464	2.6979**	4.2869
	(1.2555)	(7.0325)	(1.2400)	(6.6686)
Male	5.3245***	-113.5297***	5.5004***	598.2445***
	(1.7822)	(32.8885)	(1.7599)	(41.2599)
Constant	-40.3280***	-89.8779***	-49.7213***	212.1303***
	(4.0346)	(26.7306)	(4.0452)	(27.8184)
Analyst F.E.	No	Yes	No	Yes
Year F.E.	No	No	Yes	Yes
Observations	6,960	6,960	6,960	6,960
R2	0.5114	0.7930	0.5237	0.8139
Adjusted R2	0.5108	0.7670	0.5230	0.7905

Table 8 reports the regression output of Pessimism on high COVID level and the WFH effect. An interaction term between these two independent variables is also included. All variables are defined in Appendix I. The dependent dummy variable, Pessimism, equals one if an analyst's EPS forecast is lower than the consensus and 0 otherwise. All columns estimate the model with control variables, with 2nd to 4th columns including fixed effects, and the last two columns using logit and probit regressions. Robust standard errors are reported in parentheses. Subscripts ***,**,* indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Regressions on Pessimism with WFH effect for period 2019-2020

	Pessimism					
	OLS				Probit	Logit
	(1)	(2)	(3)	(4)	(5)	(6)
HiCOVID	0.1283***	0.0467***	0.0814***	0.0456***	0.3325***	0.5341***
	(0.0027)	(0.0032)	(0.0029)	(0.0032)	(0.0071)	(0.0114)
WFH	0.1885***	0.1558***	0.1413***	0.1574***	0.4848***	0.7788***
	(0.0037)	(0.0039)	(0.0039)	(0.0040)	(0.0097)	(0.0156)
*HiCOVID*WFH*	-0.1392***	-0.0672***	-0.0920***	-0.0661***	-0.3602***	-0.5789***
	(0.0050)	(0.0055)	(0.0051)	(0.0055)	(0.0132)	(0.0211)
GExp	-0.0001	0.0943***	-0.0004***	0.1001***	-0.0003	-0.0005
	(0.0001)	(0.0017)	(0.0001)	(0.0031)	(0.0004)	(0.0006)
Firm_Exp	-0.0008***	-0.0009***	-0.0008***	-0.0008***	-0.0022***	-0.0035***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0007)
Forecast_Age	-0.0004***	-0.0003***	-0.0003***	-0.0003***	-0.0009***	-0.0015***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00002)	(0.00003)
Porfolio_Firms	0.0015***	-0.0013***	0.0015***	-0.0013***	0.0040***	0.0064***
	(0.0001)	(0.0004)	(0.0001)	(0.0004)	(0.0003)	(0.0004)
Industries_covered	-0.0045***	0.0089***	-0.0046***	0.0089***	-0.0120***	-0.0193***
	(0.0003)	(0.0015)	(0.0003)	(0.0015)	(0.0009)	(0.0014)
Top10 Estimator	0.0133***	-0.0456***	0.0113***	-0.0452***	0.0356***	0.0573***
	(0.0016)	(0.0097)	(0.0016)	(0.0097)	(0.0044)	(0.0071)
Male	0.0052**	-2.1395***	0.0050*	-2.2710***	0.0143**	0.0226**
	(0.0025)	(0.2763)	(0.0025)	(0.2823)	(0.0068)	(0.0110)
Constant	0.4006***	-0.6380**	0.3736***	-0.6920**	-0.2525***	-0.4038***
	(0.0041)	(0.2734)	(0.0041)	(0.2745)	(0.0109)	(0.0177)
Analyst F.E.	No	Yes	No	Yes	No	No
Year F.E.	No	No	Yes	Yes	No	No
Observations	401,328	401,328	401,328	401,328	401,328	401,328
R2	0.0283	0.0654	0.0330	0.0655		
Adjusted R2	0.0283	0.0636	0.0329	0.0636		

Table 9 reports the regression output of *Pessimism* on high COVID level and the WFH effect. An interaction term between these two independent variables is also included. All variables are defined in Appendix I. The dependent dummy variable, Pessimism, equals 1 if an analyst's EPS forecast is lower than the consensus and 0 otherwise. All columns estimate the model with control variables, with 2nd to 4th columns including fixed effects, and the last two columns using logit and probit regressions. Robust standard errors are reported in parentheses. Subscripts ***,**,* indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Regressions on PMAFE with WFH effect for period 2019-2020

	PMAFE			
	OLS			
	(1)	(2)	(3)	(4)
HiCOVID	-1.4321***	-1.1181***	-1.3424***	-1.0302***
	(0.0607)	(0.0719)	(0.0651)	(0.0727)
WFH	-0.2487***	-0.0191	-0.1583*	-0.1408
	(0.0830)	(0.0879)	(0.0863)	(0.0892)
*HiCOVID*WFH*	-0.1392***	-0.0672***	-0.0920***	-0.0661***
	(0.0050)	(0.0055)	(0.0051)	(0.0055)
GExp	-0.0260***	-0.3415***	-0.0255***	-0.8116***
	(0.0031)	(0.0392)	(0.0031)	(0.0701)
Firm_Exp	0.0191***	0.0137***	0.0191***	0.0131***
	(0.0038)	(0.0046)	(0.0038)	(0.0046)
Forecast_Age	0.0076***	0.0080***	0.0076***	0.0080***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Porfolio_Firms	-0.0060***	0.0406***	-0.0060***	0.0410***
	(0.0023)	(0.0080)	(0.0023)	(0.0080)
Industries_covered	0.0403***	-0.1280***	0.0405***	-0.1273***
	(0.0074)	(0.0341)	(0.0074)	(0.0341)
Top10 Estimator	0.2162***	0.2001	0.2199***	0.1670
	(0.0366)	(0.2223)	(0.0366)	(0.2223)
Male	0.1968***	8.7298	0.1972***	19.3739***
	(0.0568)	(6.1367)	(0.0568)	(6.2756)
Constant	1.3704***	1.1086***	1.2798***	1.0221***
	(0.1124)	(0.1243)	(0.1149)	(0.1247)
Analyst F.E.	No	Yes	No	Yes
Year F.E.	No	No	Yes	Yes
Observations	385,355	385,355	385,355	385,355
R2	0.0077	0.0266	0.0078	0.0268
Adjusted R2	0.0077	0.0266	0.0078	0.0268

Table 8 reports the regression output of *PMAFE* on high COVID level and the WFH effect. An interaction term between these two independent variables is also included. All variables are defined in Appendix I. A lower value of PMAFE indicates higher forecast accuracy. All columns estimate the model with control variables, while the last three measure different fixed effects. Robust standard errors are reported in parentheses. Subscripts ***,**,* indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11: Regressions on TIMELINESS with WFH effect for period 2019-2020

	SPEED			
	OLS			
	(1)	(2)	(3)	(4)
HiCOVID	-0.6253	3.8108	4.8441	3.8915
	(4.7298)	(5.3493)	(4.8897)	(5.3507)
WFH	5.2443	1.4299	10.2305**	2.6486
	(5.0953)	(5.2784)	(5.2133)	(5.4900)
*HiCOVID*WFH*	-23.4230***	-15.8885*	-28.0675***	-16.3275*
	(8.0639)	(8.5422)	(8.1072)	(8.5602)
GExp	0.7930***	-2.5154	0.7619***	-1.2644
	(0.1788)	(1.7805)	(0.1782)	(2.3595)
Firm_Exp	-0.0557	-0.4056**	-0.1310	-0.4057**
	(0.1767)	(0.1906)	(0.1769)	(0.1906)
Forecast_Age	0.0480***	0.0428***	0.0542***	0.0431***
	(0.0083)	(0.0088)	(0.0084)	(0.0088)
Porfolio_Firms	0.3657*	-0.6425	0.4208**	-0.5795
	(0.1952)	(0.5243)	(0.1949)	(0.5301)
Industries_covered	-2.2263***	-1.3421	-2.2414***	-1.4083
	(0.6637)	(2.2581)	(0.6609)	(2.2598)
Top10 Estimator	-13.6364***	18.0497	-12.8355***	24.0193
	(2.8271)	(19.9366)	(2.8218)	(21.2628)
Male	-7.5529***	-39.9839	-7.7138***	-12.0605
	(2.5016)	(43.9442)	(2.4914)	(55.9043)
Constant	52.7722***	118.6737**	53.6781***	79.9129
	(4.6892)	(59.1277)	(4.6746)	(76.1386)
Analyst F.E.	No	Yes	No	Yes
Year F.E.	No	No	Yes	Yes
Observations	1,947	1,947	1,947	1,947
R2	0.0633	0.1201	0.0716	0.1204
Adjusted R2	0.0585	0.1049	0.0664	0.1048

Table 11 reports the regression output of SPEED on high COVID level and the WFH effect. All variables are defined in Appendix I. A higher value of SPEED indicates better timeliness. All columns estimate the model with control variables, while the last three columns also measure different fixed effects. Robust standard errors are reported in parentheses. Subscripts ***,**,* indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12: Regressions on Frequency with WFH effect for period 2019-2020

	Frequency			
	OLS			
	(1)	(2)	(3)	(4)
quar_HiCOVID	-13.1206***	-15.4926***	-28.9274***	-16.9014***
	(1.8536)	(1.6311)	(2.1287)	(1.5585)
days_WFH	0.4616***	0.4500***	-0.0271	0.0027
	(0.0530)	(0.0414)	(0.0622)	(0.0431)
quar_HiCOVID days_WFH*	-0.7981***	-1.0973***	0.0621***	-0.1856***
	(0.0168)	(0.0116)	(0.0197)	(0.0116)
GExp	-0.1025***	1.0698***	-0.1094***	-6.6569***
	(0.0257)	(0.2678)	(0.0253)	(0.3902)
Firm_Exp	0.0844	0.8798**	0.0836	0.2929
	(0.1102)	(0.3600)	(0.1088)	(0.3445)
Forecast_Age	0.1859***	0.2500***	0.2022***	0.1612***
	(0.0177)	(0.0181)	(0.0175)	(0.0176)
Porfolio_Firms	5.4057***	4.7564***	5.3954***	4.7583***
	(0.0790)	(0.1776)	(0.0779)	(0.1696)
Industries_covered	1.3377***	-0.2119	1.3369***	-0.2283
	(0.2789)	(0.7168)	(0.2752)	(0.6845)
Top10 Estimator	2.2259*	-0.2859	2.4382**	0.2984
	(1.2213)	(6.9171)	(1.2054)	(6.6052)
Male	-0.0003	-0.0108	0.4834***	0.2992***
	(0.0636)	(0.0513)	(0.0711)	(0.0504)
Constant	-36.2346***	-79.8904***	-45.6595***	216.7135***
	(4.0861)	(27.1779)	(4.0845)	(28.3109)
Analyst F.E.	No	Yes	No	Yes
Year F.E.	No	No	Yes	Yes
Observations	7,879	7,879	7,879	7,879
R2	0.5195	0.8024	0.5321	0.8198
Adjusted R2	0.5189	0.7807	0.5314	0.8000

Table 12 reports the regression output of Forecast Frequency on high COVID level and the WFH effect. All variables are defined in Appendix I. A higher value of Forecast Frequency indicates a higher number of forecasts issued. The COVID severity is the average of quarter, the proxy for WFH is *days_WFH*, measuring the number of days analysts have to telecommute in the quarter. All columns estimate the model with control variables, while the last three measure different fixed effects. Robust standard errors are reported in parentheses. Subscripts ***,**,* indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 13 : Firm Exposure to COVID-19

	Pessimism				PMAFE	
	OLS		Probit	Logistic	OLS	
	(1)	(2)	(3)	(4)	(5)	(6)
HiCOVID	0.102***	0.066***	0.263***	0.422***	-0.488***	-0.411***
	(0.0020)	(0.0020)	(0.0060)	(0.0090)	(0.0490)	(0.0530)
Covid_Exposure	0.044***	0.032***	0.115***	0.184***	-0.276***	-0.168***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0200)	(0.0200)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.393***	-0.298	-0.272***	-0.435***	0.564***	6.902
	(0.0040)	(0.2750)	(0.0110)	(0.0180)	(0.0980)	(6.1910)
Analyst F.E.	No	Yes	No	No	No	Yes
Year F.E.	No	Yes	No	No	No	Yes
Observations	365,355	365,355	365,355	365,355	350,692	350,692
R2	0.028	0.065			0.008	0.030
Adjusted R2	0.028	0.063			0.007	0.028

Table 13 reports the regression output of Pessimism and PMAFE, respectively, on high COVID severity level and other control variables. Here, I specifically add the control variable *Covid_exposure* to control for the fundamental effects that the pandemic may have on firms. All variables are defined in Appendix I. Control variables are untabulated. Pessimism equals 1 indicates a pessimistic forecast, and a lower value of PMAFE indicates higher forecast accuracy. Robust standard errors are reported in parentheses. Subscripts ***,**,* indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 14: Exlcuding NY State

	Pessimism				PMAFE	
	OLS		Probit	Logistic	OLS	
	(1)	(2)	(3)	(4)	(5)	(6)
HiCOVID	0.1672***	0.1169***	0.4311***	0.6928***	-1.4568***	-1.2877***
	(0.0000)	(0.0000)	(0.0100)	(0.0200)	(0.0700)	(0.0900)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.3240***	0.8213***	-0.4571***	-0.7348***	-0.0444	-0.2897
	(0.0100)	(0.2100)	(0.0200)	(0.0400)	(0.1600)	(3.7800)
Analyst F.E.	No	Yes	No	No	No	Yes
Year F.E.	No	Yes	No	No	No	Yes
Observations	101,037	101,037	101,037	101,037	96,759	96,759
R2	0.0276	0.0553			0.0163	0.0372
Adjusted R2	0.0276	0.0535			0.0162	0.0353

Table 14 reports the regression output of Pessimism and PMAFE, respectively, on high COVID level and other control variables. Forecasts made by analysts located in New York state are excluded in these regressions. All variables are defined in Appendix I. Control variables are untabulated. Pessimism equals 1 indicates a pessimistic forecast, and a lower value of PMAFE indicates higher forecast accuracy. Robust standard errors are reported in parentheses. Subscripts ***,**,* indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 15: Including only analysts appear in both years

	Pessimism				PMAFE	
	OLS		Probit	Logistic	OLS	
	(1)	(2)	(3)	(4)	(5)	(6)
HiCOVID	0.1473***	0.0908***	0.3785***	0.6076***	-0.7469***	-0.5821***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.04)	(0.05)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.4162***	0.1339**	-0.2116***	-0.3371***	0.4610***	7.1129***
	(0.00)	(0.06)	(0.01)	(0.02)	(0.09)	(1.30)
Analyst F.E.	No	Yes	No	No	No	Yes
Year F.E.	No	Yes	No	No	No	Yes
Observations	376,945	376,945	376,945	376,945	362,000	362,000
R2	0.0224	0.0581			0.0073	0.0266
Adjusted R2	0.0224	0.0565			0.0073	0.0249

Table 15 reports the regression output of Pessimism and PMAFE, respectively, on high COVID level and other control variables. Analysts who exit after 2019 and enter in 2020 are excluded. All variables are defined in Appendix I. Control variables are untabulated. Pessimism equals 1 indicates a pessimistic forecast, and a lower value of PMAFE indicates higher forecast accuracy. Robust standard errors are reported in parentheses. Subscripts ***,**,* indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 16: Excluding Terrorism and Extreme Weather Effects

	Pessimism				PMAFE	
	OLS		Probit	Logistic	OLS	
	(1)	(2)	(3)	(4)	(5)	(6)
HiCOVID	0.1271***	0.0761***	0.3243***	0.5196***	-0.4960***	-0.3433***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.05)	(0.05)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.3950***	-0.1671	-0.2672***	-0.4278***	0.7604***	5.4526
	(0.00)	(0.28)	(0.01)	(0.02)	(0.11)	(6.01)
Analyst F.E.	No	Yes	No	No	No	Yes
Year F.E.	No	Yes	No	No	No	Yes
Observations	290,706	290,706	290,706	290,706	280,039	280,039
R2	0.016	0.0602			0.0046	0.0223
Adjusted R2	0.016	0.0577			0.0046	0.0196

Table 16 reports the regression output of Pessimism and PMAFE, respectively, on high COVID level and other control variables. Forecasts made around severe weather events and terrorism are excluded. All variables are defined in Appendix I. Control variables are untabulated. Pessimism equals 1 indicates a pessimistic forecast, and a lower value of PMAFE indicates higher forecast accuracy. Robust standard errors are reported in parentheses. Subscripts ***,**,* indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 17: Placebo Test

	Pessimism				PMAFE	
	OLS		Probit	Logistic	OLS	
	(1)	(2)	(3)	(4)	(5)	(6)
HiCOVID	-0.0005	-0.0003	-0.0014	-0.0022	0.0441	0.0395
	(0.00)	(0.00)	(0.01)	(0.01)	(0.04)	(0.04)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.4429***	-0.0432	-0.1425***	-0.2263***	0.0918	4.0606
	(0.00)	(0.27)	(0.01)	(0.02)	(0.09)	(6.07)
Analyst F.E.	No	Yes	No	No	No	Yes
Year F.E.	No	Yes	No	No	No	Yes
Observations	401,328	401,328	401,328	401,328	385,355	385,355
R2	0.0070	0.0552			0.0063	0.0259
Adjusted R2	0.0070	0.0534			0.0063	0.0239

Table 17 reports the regression output of Pessimism and PMAFE, respectively, on high COVID level and other control variables. Levels of COVID severity are randomized across dates and states. All variables are defined in Appendix I. Control variables are untabulated. Pessimism equals 1 indicates a pessimistic forecast, and a lower value of PMAFE indicates higher forecast accuracy. Robust standard errors are reported in parentheses. Subscripts ***,**,* indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 18: Firms' Characteristics

	Pessimism				PMAFE	
	OLS		Probit	Logistic	OLS	
	(1)	(2)	(3)	(4)	(5)	(6)
HiCOVID	0.1431***	-0.0003	-0.0014	-0.0022	0.0441	0.0395
	(0.0019)	(0.00)	(0.01)	(0.01)	(0.04)	(0.04)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.4429***	-0.0432	-0.1425***	-0.2263***	0.0918	4.0606
	(0.0000)	(0.2700)	(0.0100)	(0.0200)	(0.0900)	(6.0700)
Market Value	0.0000***	0.0000***	0.0000***	0.0000***	-0.0001***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Size	-0.0087***	-0.0082***	-0.0095***	-0.0102***	0.1488***	0.1268***
	(0.0005)	(0.0005)	(0.0007)	(0.0009)	(0.0122)	(0.0255)
Profitability	-0.3168***	-0.2001**	-0.4167***	-0.5129***	-5.1583***	-4.8300*
	(0.0133)	(0.0300)	(0.0212)	(0.0215)	(0.3035)	(0.4520)
Ln(Turnover)	0.0023	0.0015	0.0037	0.0036	-2.1011	-1.8707
	(0.0111)	(0.051)	(0.0300)	(0.0301)	(0.1050)	(0.1080)
Stock price	0.0000	0.0001	0.0000	0.0000	-0.0000	-0.0000
	(0.0020)	(0.0355)	(0.0150)	(0.0215)	(0.3749)	(0.3547)
Analyst F.E.	No	Yes	No	No	No	Yes
Year F.E.	No	Yes	No	No	No	Yes
Observations	381,116	381,116	381,116	381,116	366,068	366,068
R2	0.0200	0.0450			0.0058	0.0201
Adjusted R2	0.0200	0.0430			0.0051	0.0108

Table 18 reports the regression output of Pessimism and PMAFE, respectively, on high COVID level and other control variables. Here I include key firms' fundamentals, namely, Market Value, Size, Profitability, ln(Turnover) and Stock Price as added control variables. All variables are defined in Appendix I. Control variables are untabulated. Pessimism equals 1 indicates a pessimistic forecast, and a lower value of PMAFE indicates higher forecast accuracy. Robust standard errors are reported in parentheses. Subscripts ***,**,* indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.