Team versus individual: Evidence from financial analysts during COVID-19 pandemic *

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Abstract

This paper investigates whether the performance of teams is better than that of individuals during crisis times. I look at one important type of team in the financial market, the financial analyst team, and take advantage of the exogenous shock introduced by stay-at-home orders in the United States during the COVID-19 pandemic, to examine the forecast timeliness and accuracy differences between team analysts and individual analysts. I find that teams and individual analysts perform worse during the working from home period than they do in normal times but on average teams perform better than individual analysts do: team analysts can issue more timely forecast compared to individual analysts without the loss of forecast accuracy. In addition, team size plays an important role in teams' performance. A further test shows that investors react more to teams' forecasts issued during the pandemic than individual's forecasts. In summary, this paper provides new evidence on the performance difference between teams and individuals, especially during tough times.

Keywords: Financial analysts; Team performance; Forecast timeliness; COVID-19

JEL Classification: G24; G41

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1 Introduction

Teams are popular in many economic activities. Top management teams of companies work together to make decisions (Graham et al. (2015)); mutual fund management teams that become more and more popular in the industry make investment decisions together (Bär et al. (2011); Chen et al. (2020)); financial analysts work as teams to research their portfolio firms (Fang and Hope (2021)). Although these studies pay a lot of attention to teams, they just compare the team's and individual's performance during normal times. Little attention, however, is paid to the difference of performance between team and individual during tough and crisis periods. The investigation of this question can deepen our understanding of the differences between teams and individuals. The empirical challenge of this question is that an exogenous shock that systematically, massively, and negatively affects the universal teams and individuals is rare. In this paper I overcome this challenge by taking advantage of the exogenous working from home policy caused by stay-at-home orders during the COVID-19 pandemic to examine whether financial analyst teams perform better than individual analysts during crisis times.

I use the financial analysts during the COVID-19 pandemic as the laboratory in this paper because it has several distinct advantages. Firstly, financial analyst teams are popular in the industry. Fang and Hope (2021) find that approximately 70% of analysts are actually analyst teams, although I/B/E/S records most of them as individual analysts. As an information intermediary in the financial markets, analysts are central to the flow of information between firms and investors. They collect information, analyze and interpret it, and finally disseminate it by making recommendations, providing forecasts, and writing reports. Understanding the performance difference between analyst teams and individuals has implications for both the analysts industry and the whole financial market. Secondly, there are rich and observable data on financial analysts. I/B/E/S allows me to measure the performance of analysts' activities precisely. Meanwhile, biographic information of analysts is also available online, e.g., LinkedIn, BrokerCheck, and company websites. The availability of analyst team members' biographic data helps me measure the team's characteristics. Finally, the unexpected stay-at-home order across U.S. states starting from March 2020 is a plausible setting to satisfy the empirical analyses requirements. It is exogenous and unanticipated to the universal market players. The stay-at-home order makes the analysts work from home, which largely and negatively affects the working style of employees. I compare the performance of analyst teams with the performance of individual analysts in this paper. The underlying identification assumption is that I treat the composition of analyst teams before the stay-at-home order as exogenous with respect to the shock. As a result, I essentially compare differences in responses between the team and individual analysts whose composition is predetermined before the shock.

The analyst performance measures I investigate are forecast timeliness and forecast accuracy that are commonly used in the previous literature. Timely forecasts are crucial to investors and the market. On the one hand, the timely forecast has a greater impact on stock prices than follower analysts and is more informative, and therefore valued by investors (Cooper et al. (2001)). On the other hand, the forecast timeliness could improve market efficiency in the sense that they facilitate price discovery (Zhang (2008)). The accuracy of forecasts, considered as the most-researched dimension of forecast performance, is also important to the market (Brown and Hugon (2009)). More importantly, using the forecast timeliness and accuracy to gauge the performance of analysts fits the setting of the working from home policy caused by the stay-at-home order. To make a timely and accurate forecast, analysts should collect enough new information and respond fast to new information. However, during the lockdown, it becomes difficult for analysts to collect information from firms, work together with colleagues to analyze the information, and issue timely forecasts. Therefore, the focus on the forecast timeliness and accuracy helps investigate whether teamwork is more valuable than individual work during tough times.

The sample period I choose is the first three quarters of 2020. Most of the stay-at-home orders were announced at the end of the first quarter or the beginning of the second quarter of 2020, which means that my sample period consists of almost one quarter period before the event and two quarters after the event. I do not choose a longer sample period after the event but ends on August 31st to eliminate the confounding factors that could affect analysts' behavior. I download analysts' forecasts for U.S. firms during the sample period from I/B/E/S and filter the sample following previous studies (e.g., DeHaan et al. (2015); Driskill et al. (2020)).

To identify whether forecasts are issued by analyst teams or individual analysts, I follow the method developed in Fang and Hope (2021). Although I/B/E/S database indicates whether forecasts or recommendations are made by individual analysts or by analyst teams, it is not accurate according to previous studies (Brown and Hugon (2009); Fang and Hope (2021)). Instead, I rely on the analyst research reports that include the detailed authors' information. Specifically, I match the corresponding analyst research reports for each analyst forecast recorded in I/B/E/S to check whether the forecast is made by an individual analyst or by an analyst team. If the number of authors for a forecast's corresponding report is more than one, I treat the analyst who issues that forecast as an analyst team and assign one to dummy variable *Team*, otherwise, it is an individual analyst and *Team* is zero. Using this method, I find that the analyst team makes about 57% of forecasts in my sample. This figure is much larger than that in I/B/E/S.

To check whether forecasts are issued before the stay-at-home orders, I link analyst names retrieved from analyst research reports to the registration data in FINRA BrokerCheck.[1] BrokerCheck provides the historical registration information for analysts that includes the location of the brokerage houses branch offices. I create a dummy variable *WFH* which is one if the time when the analyst issues a forecast is later than the working from home policy in the state where the analyst is located and zero otherwise.

My final sample consists of 12,249 forecasts issued by 1,301 individual and team analysts for 1,475 firms in the first three quarters of 2020. Among them, 57% are issued by teams and 69% are issued after the working from home policy.

I apply the difference-in-differences (DID) strategy to examine whether working from home affects the forecast timeliness and accuracy differently between teams and individual analysts. Specifically I regress the analyst performance measures on *WFH* and interaction term *Team* $\times$ *WFH*. A host of analyst and brokerage control variables are included following previous studies (Driskill et al. (2020); Du (2020)). In all specifications I include the *Firm* $\times$ *Fiscal Quarter* fixed effects, which helps me to compare the forecast timeliness likelihood between team analysts and individual analysts by requiring them to do the same tasks: making forecasts for the same firm's earnings of the same fiscal quarter. In the strictest specification I include *Analyst* $\times$ *Firm* fixed effects and *Year-month* fixed effects.

The baseline results show that after the stay-at-home order, the likelihood of issuing a timely forecast and the forecast accuracy decrease for both individual and team analysts. In contrast, team analysts are more likely to issue a timely forecast compared with individual analysts. The estimated coefficient on the interaction term *Team* $\times$ *WFH* is between 3.7% and 4.1% and is statistically significant at least at the 5% level. In addition, teams' releasing timely forecasts does not affect forecast accuracy. I do not find significant differences in forecast accuracy between teams and individuals after the implementation of the working from home policy. Previous literature documents that individuals outperform teams with respect to earnings forecast accuracy during regular times (Brown and Hugon (2009)). My result is evident to the argument that

[1]See https://brokercheck.finra.org/

individuals perform worse compared to analysts during difficult times.

A further dynamics DID test provides additional evidence. I firstly extend the sample period to the third quarter of 2019 and split this new sample period into five subperiods: 2019 third quarter (*2019Q3*), 2019 fourth quarter (*2019Q4*), 2020 first quarter (*2020Q1*), 2020 second quarter (*2020Q2*), and 2020 third quarter (*2020Q3*). I run regression specifications that are similar to those in the baseline but replace the term *Team* × *WFH* by the interactions of subperiod dummy variables and *Team*. The results show that the effect of working from home on forecast timeliness differences between teams and individual analysts only exists after the event: only the estimated coefficients are significantly positive only for *Team* × *2020Q2*. For forecast accuracy, I find that teams perform better and better over time during the working from home period. I find no significant estimated coefficient on *Team* × *2020Q2* but a significant coefficient on *Team* × *2020Q3*.

Previous literature documents the crucial role of team size on teams performance (Cheng (2008); Patel and Sarkissian (2017)). COVID-19 working from home policy provides a plausible setting for me to test whether team size could affect team performance since the pandemic is unanticipated to the whole market players and the team size before the COVID-19 pandemic working from home policy is exogenous. I expect that the forecast timeliness increases with the team size because timely forecasts need fast responses to new information. The more members, the lower the probability of being distracted by working from home. Forecast accuracy needs more communication and coordination between team members. Therefore, there is a trade-off of the benefits and costs of team sizes. I thus posit that the relationship is nonlinear and that there exists an optimal team size. To empirically test these hypotheses, I repeat the same analysis as the baseline but replace the dummy variable *Team* by the team size. I also add a quadratic term of team size in the regression specifications to test whether there is optimal team size. The empirical results support my expectations. I find a monotonic positive relationship between the team size and forecast timeliness and a U-shaped relationship between the team size and forecast accuracy.

Finally, I provide additional analyses on relevant questions. Firstly, I check the robustness of my results by comparing the timeliness and accuracy of forecasts made from March 2020 to August 2020, when almost all U.S. states announced the stay-at-home orders, with the timeliness of forecasts made in the same period in 2019. This robustness test can help to rule out the seasonality of forecasts (Lo and Wu (2018)). I find very similar results that further confirm the findings in the baseline. Secondly, I examine an important question whether team analysts improve market efficiency if they can issue more timely forecasts compared to individual analysts. I first show that team analysts and individual analysts actually can issue similar timely forecasts if I use a continuous measure of forecast timeliness, the day gap between the forecast announcement day and the earnings announcement day. This result seems to imply that teams' forecasts cannot improve market efficiency since their forecasts are just a little earlier than individuals' forecasts but with similar accuracy. Next, I look at the market reaction to measure whether investors care more about teams' forecasts. I regress cumulative abnormal returns around the forecast announcement day on *Team* and interaction term $Team \times WFH$ and other controls. The results show that investors' reaction to teams' forecasts during the working from home period is larger than that to forecasts issued by individual analysts. From the investors perspective, teams' forecasts are more informative and can improve market efficiency, especially during tough times. The last set of additional exercises considers other dimensions of analyst performance: forecast updating frequency and length of the analyst research reports. Using the same method as the baseline analysis, I also find that team analysts issue fewer updating forecasts while writing longer analyst research reports compared to individual analysts after stay-at-home orders.

This paper contributes to several strands of literature. First, it contributes to the study of the differential performance between teams and individuals. Most of these studies focus on small sample groups (Boning et al. (2007); Delfgaauw et al. (2022); Hamilton et al. (2003)). Some studies in this literature are based on experimental evidence (Auerswald et al. (2018); Cooper and Kagel (2005)). Studies on performance of teams in the finance literature are concentrated on mutual fund managers (Adams et al. (2018); Bär et al. (2011); Luo and Qiao (2020)) and board of directors (Ahern and Dittmar (2012); Bernile et al. (2018)). Fewer studies investigate the financial analyst teams' performance. Fang and Hope (2021) is one exception that systematically compares the performance of team analysts and individual analysts and shows that analyst teams generate more accurate earnings forecasts than individual analysts. The main problem of these studies is that they usually compare the team and individual performance during normal time. Also they do not fully consider the endogenous team composition issue, which may make their results biased. In this paper I provide new evidence on the performance of analyst teams during difficult times. More importantly, I exploit the stay-at-home order caused by the COVID-19 pandemic as an exogenous shock to the team composition and compare the performance of analyst teams and individual analysts.

Second, it contributes to the literature of COVID-19. As Kniffin et al. (2021) points out, research should examine whether and how the COVID-19 quarantines that require millions to work from home affect work productivity, creativity, and innovation. In this paper I use financial analysts as the setting and find that working from home during the COVID-19 pandemic largely and negatively affects financial analysts' work patterns, productivity, and performance. More importantly, I show that this negative effect is more pronounced for individual analysts.

Third, my study contributes to the literature on the impact of working from home on productivity. Working from home becomes common both in the U.S. and other countries even before the COVID-19 pandemic (Bloom et al. (2015); Mateyka et al. (2012)). Whether working from home is a useful management practice for raising productivity is an important question for managers and companies. The current studies on this question concentrate on the field experiment and laboratory experiment because it is challenging to run a mass social experiment in working from home. These experimental studies provide mixed results. For example, Bloom et al. (2015), run a field experiment in a large NASDAQ-listed Chinese travel agency firm and find that working from home improves the performance. While Dutcher (2012) uses an experimental approach and finds that the telecommuting environmental effects may have positive implications on the productivity of creative tasks but negative implications on the productivity of dull tasks. The unexpected COVID-19 pandemic triggers a mass social experiment in working from home (Barrero et al. (2021)). I take advantage of this shock, focus on the financial analysts, and find that, on average, working from home is harmful to the financial analyst, who requires massive communication and cooperation.

Lastly, it contributes to the studies of analysts' performance. Analyst forecast timeliness and accuracy are important performance perspectives for the investor, market efficiency, and the analysts' career (Chiu et al. (2021); Cooper et al. (2001)); Zhang (2008)). Previous literature shows that the analyst forecasts timeliness are negatively affected by limited attention (Driskill et al. (2020)). I provide empirical evidence for a new channel: the exogenous working from home policy caused by the COVID-19 pandemic. This paper is closely related to Du (2020) and Li and Wang (2021) that also use the COVID-19 pandemic as the experiment to investigate the analyst forecast timeliness and accuracy, while they focus on the difference between male and female analysts during the pandemic due to the domestic burdens on female analysts' attention.

The remainder of the paper is structured as follows. I briefly introduce the institutional background in Section 2. In Section 3 I review the literature and develop hypotheses. Section

4 discusses the data sources and provides summary statistics for the main variables. Section 5 presents the main empirical results. I do additional analyses in Section 6. Finally, I conclude in Section 7.

2 Institutional Background

In this section I discuss the institutional background of financial analyst teams and COVID-19 working from home policy. I benefit a lot from Bradshaw et al. (2017a) and Groysberg and Healy (2013) on the sell-side equity analysts industry, especially the characteristics of analyst teams. Kniffin et al. (2021) provide an excellent review of the impacts of COVID-19 on workers and workplaces.

2.1 Analyst Teams

Although extant literature investigates the role of sell-side equity analysts in capital markets, most studies do not consider that sell-side equity analysts often work in teams (Gao et al. (2021)). However, analysts generally work in teams according to academic findings and anecdotal evidence. For example, Fang and Hope (2021) find that analyst teams issue more than 70% of annual earnings forecasts using a hand-collected sample of over 50,000 analyst research reports. Anecdotal evidence from the financial analysts industry shows that "analysts and their juniors function as a team, with the analyst's name at the top of all work products." (Groysberg and Healy (2013)). Julie Yates Stewart was selected as a Rising Star of Wall Street in 2014. She talked about her cooperation with another analyst Robert Spingarn and said: "We've really run this franchise as a team over the past couple of years ... [Robert and I] leverage the expertise from each other."[2]

A typical analyst team consists of a lead analyst and additional associate analysts. The lead analyst who bears the overarching responsibility for the team's performance leads the team, provides the general guidelines and framework for modeling, communicates with clients, and interacts with the brokerage house's management. Associates are apprentices working as part of a support team for the lead analyst. Their main role is to prepare earnings models, valuation models, reports, and presentations. In other words, associates perform most of the grunt work of number-crunching financial models. Most academic research focuses on the quantitative outputs

[2] See https://www.institutionalinvestor.com/article/b14zblbkq2h2mb/the-2014-rising-stars-of-wall-street

from this process, typically earnings forecasts and valuation-based metrics such as stock recommendations and target prices. These necessary outputs are largely produced by associates, who are not named analysts on common research databases like I/B/E/S.

2.2 COVID-19 and Working from Home Policy

Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), the virus that causes coronavirus disease 2019 (COVID-19), is thought to spread from person to person primarily by the respiratory route and mainly through close contact.[3] Governments around the world attempt to control the COVID-19 pandemic by deploying a wide range of nonpharmaceutical interventions, including stay-at-home orders and the closure of all nonessential businesses (Ruktanonchai et al. (2020)). In the United States, local jurisdictions implement stay-at-home orders in a staggered manner over time and geographies, without national coordination. Until 2020 May 31st, 42 states and territories issued mandatory stay-at-home orders (Moreland et al. (2020)).

The mandatory stay-at-home orders have resulted in a massive shift in the number of employees working from home. According to survey data from Bick et al. (2020), working from home increases sharply and persistently after the outbreak of the COVID-19 pandemic: the fraction of the workforce working from home increased from roughly 8% in February 2020 to more than 35% by May of 2020. Another study by Brynjolfsson et al. (2020) shows a similar result. They ran a two-wave survey in April and May 2020 for a nationally-representative sample of the US population during the COVID-19 pandemic. Results show that about half of respondents are now working from home, including 35.2% who report they were commuting and recently switched to working from home. In addition, 10.1% report being laid-off or furloughed since the outbreak of the COVID-19 pandemic.

The COVID-19 pandemic and working from home abruptly upend regular work routines, which presumably has a serious impact on both employees and employers (Bolisani et al. (2020)). As an important player in the financial service industry, the sell-side analyst is largely affected by working from home undoubtedly. *Institutional Investor* asked a number of sell-side analysts to share their experience during COVID-19 crisis.[4] Almost everyone interviewed analysts mention the increase in virtual communication with clients, corporates, and colleagues. Some pointed to the ability to spend more time with their families. These real-life experiences have been discussed

[3] See https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/how-covid-spreads.html

[4] See https://www.institutionalinvestor.com/article/b1nv1zts9361bl/How-the-Coronavirus-Crisis-Changed-Investment-Research-According-to-the-All-America-Research-Team

in academics. Ramarajan and Reid (2013) point out that employees often find it challenging to maintain boundaries between work and nonwork. Recent studies by Du (2020) and Li and Wang (2021) find that analysts' attention is distracted by domestic work after the closure of schools after the outbreak of the COVID-19 pandemic.

3 Hypotheses Development

There are different analysts' performance activities. Forecast timeliness and accuracy are two important angles to assess the quality of analyst earnings forecasts. The forecast timeliness is closely related to the investor and the market efficiency. Firstly, according to the study by Cooper et al. (2001), lead analysts making the timely forecast have a greater impact on stock prices than follower analysts. Further, they find that the timely forecasts are more informative. Therefore, investors care about the timeliness of forecasts. Secondly, the forecast timeliness could improve market efficiency. Zhang (2008) argues that if analysts' forecast revisions fully reflect prior earnings news but are only made long after the information becomes available, such revisions are not efficient in time, which makes the forecast revisions still inefficient. Thus, timely forecasts are crucial to market efficiency because they facilitate price discovery. The accuracy of forecasts which is considered as the most-researched dimension of forecast performance is also important to the market (Brown and Hugon (2009)). Therefore, I use it as the main performance measure for analysts in this paper.

To make a timely and accurate forecast, analysts should respond to new information released by portfolio firms in the earnings announcement events. If analysts have limited attention due to distractions or other reasons, collecting and reacting to newly arrived information is more challenging. As a result, they are less likely to issue timely and accurate forecasts. The source of attention distractions could be multiple. For example, Du (2020) finds novel empirical evidence that female analysts are more distracted from domestic duties after school closures caused by the COVID-19 pandemic. As a result, female analysts issue less timely forecasts compared to males. Li and Wang (2021) find that female analysts' forecast accuracy declined more than male analysts during the COVID-19 pandemic period. They also attribute the performance decline in female analysts to childcare and household duties.

Although some workers are clearly enthusiastic about working from home, the value implications to financial analysts' performance, especially the forecast timeliness, are perhaps negative. Proponents of working from home argue that it can enhance workers' performance by increasing worker productivity due to eliminating commuting and minimizing distractions. However, these benefits of working from home are not applied to analysts because of the features of analysts' work. Financial analysts usually work as a team. Team members act their roles, and communication between them is crucial to the final outcomes. According to the interview with the financial analyst in Wall Street, a typical day for financial analysts is that they spend time in the office with colleagues discussing ongoing work following the market opening (Groysberg and Healy (2013)). The benefits of working from home may not apply to the analyst, while the dark side of working from home exists. Working from home can encourage shirking, reduce focus, limit opportunities for valuable collaboration. Working from home also can distract analysts' attention. Employees often find it is a challenge to maintain boundaries between work and non-work (Ramarajan and Reid (2013)). One example is that female analysts have to spend more time on domestic work after school closures due to the COVID-19 (Du (2020); Li and Wang (2021)). Therefore, I propose the first hypothesis.

H1: *Analyst forecast timeliness likelihood and forecast accuracy decrease after working from home caused by the stay-at-home orders during COVID-19 pandemic.*

Although, on average, I expect that working from home could reduce the analysts' forecast likelihood of issuing timely forecasts and the accuracy of forecasts, the effect may be different for team analysts and individual analysts. Becker and Murphy (1992) argue that teamwork allows a more extensive division of labor and improved productivity. In the financial analyst setting, analyst teams usually divide the labor into different groups and each member takes care of one aspect of the research work. In Wall Street, the lead analyst of the analyst team puts more effort into communicating with clients and management of covered companies, while the associate analysts focus on the modeling tasks (Groysberg and Healy (2013)). This specialized labor division can improve the return to the time and resources spent on the individual tasks and therefore improve the overall performance of the team (Fang and Hope (2021)). Even if one team member is distracted when working at home, other team members are still working on their own work. As a result, the probability that all team members are distracted decreases. In contrast, if an individual analyst is distracted by domestic work, no one else can help her when she works at home alone. Thus, I make the second hypothesis as follows:

H2: *Team analysts' timely forecasts likelihood is higher than that of individual analysts when analysts work from home due to the stay-at-home order.*

With respect to the forecast accuracy, the expected outcome is not so clear. Previous studies document mixed results on the relationship between teams and forecast accuracy. Brown and Hugon (2009) show that teams are less accurate than individual analysts in general. However, Fang and Hope (2021) documents that analyst teams generate more accurate earnings forecasts than individual analysts and that the stock market reacts more strongly to forecast revisions issued by teams. Although the mixed results could be attributed to different samples and different methodologies to identify team analysts, the relationship between team and forecast accuracy is still unclear. It is interesting to examine whether teams can perform better compared to individual analysts with respect to forecast accuracy especially during tough times.

Previous literature documents the significant role of team size on performance (e.g., Cheng (2008)). As I analyze above, timely forecasts need a fast reaction to new information. More members are positive to collecting information and quick reaction since the probability that all analysts are distracted is lower. Therefore, I make the following hypothesis on the relationship between team size and forecast timeliness.

H3a: *Team analysts' timely forecasts likelihood monotonically increases with the increase of team size when analysts work from home due to the stay-at-home order.*

On the other hand, making accurate forecasts needs assimilation and evaluation of information (Cooper et al. (2001)), which requires more coordination between team members compared to issuing timely forecasts. A larger team, however, could also increase the communication costs. Therefore, I expect that team size is nonlinearly related to forecast accuracy. Intuitively, the number of team members determines the trade-off between the larger knowledge base of more people and the coordination costs among multiple individuals (Mueller (2012)). Therefore, my last hypothesis is as follows:

H3b: *Team analysts' forecast accuracy is nonlinearly associated with the team size when analysts work from home due to the stay-at-home order.*

4 Data and Summary Statistics

4.1 Sample

Table 1 summarizes the sample construction process. The initial sample is earnings announcement events for U.S. firms downloaded from I/B/E/S Actuals database. I restrict the sample with earnings announcements in the first three quarters of 2020 because the primary analysis is around the COVID-19 stay-at-home policy started in March 2020. Following previous literature (DeHaan et al. (2015); Driskill et al. (2020)), I make the following data filtering processes. First, I exclude firm-quarters for which the earnings announcement date is more than 90 days after the fiscal quarter-end. Second, I merge the data with CRSP and Compustat to obtain the accounting and stock price information and keep the matched observations. I then drop a firm-quarter if the stock price at the fiscal end of the quarter is below 1$ to avoid extremely illiquid stocks.

I download analyst forecasts from I/B/E/S Details database. I limit the forecasts sample to one-quarter-ahead EPS forecasts (fpi = 6). I refer to the quarter whose earnings have just been announced as quarter q, and I am interested in analyst earnings forecasts for quarter $q + 1$. I require the sample of firm-quarter observations to have earnings announcement dates for both quarters q and $q + 1$. After merging forecasts observations with the cleaned earnings announcement dataset, I keep those forecasts issued after quarter q earnings announcement but one day prior to the earnings announcement of quarter $q + 1$.

Next, I link the I/B/E/S earnings announcement–forecast data set to analyst names data downloaded from I/B/E/S Recommendation database. Although analyst names in I/B/E/S Recommendation are masked, they still contain last names and first initials. To correctly identify analysts, I require that the analyst name of the forecast is non-missing. I also exclude the forecasts made by the research department or made by more than one analyst. It is because the team analyst names provided by I/B/E/S are not accurate. Furthermore, I/B/E/S only records the last names of team analyst members, which makes it is difficult to identify the analysts within the same brokerage house.

After these filtering procedures, the cleaned I/B/E/S forecasts sample consists of 70,274 firm-quarter analyst forecasts observations issued by 2,272 analysts for 3,676 companies.

4.2 Individual versus Team Analysts

To identify whether the forecast is made by the team or not, I follow the method used in Fang and Hope (2021). They manually search the analyst research report associated with each forecast issuance in Investext. To follow their method, I first download the metadata of analyst research reports for U.S. public firms in 2020 from Thomson Reuters Eikon.[5] There are a total of 103,692 unique analyst research reports written by 4,723 analysts for 5,266 distinct firms. The metadata

[5]My main empirical analysis focus on the performance of analysts in 2020. However, I download all analyst research reports metadata from 2019 to 2020 for additional analyses.

of each report includes the following information: a unique report document identifier (DCN), the name(s) of analyst(s) who write the report, the name of the contributor, the covered firm name, the covered firm ticker-liked identifier (RIC), the title, the table of content of the report, and the analyst research reports released date.[6] The detailed metadata helps me to link the forecasts sample to the analyst research reports sample by comparing the analyst's last name, the analyst's first name initial, the brokerage house name, the firm identifier, and the date in both data sets. To be a valid match, I require that (i) the affiliated brokerage house of forecast analyst and report analyst are same; (ii) the forecast and the report are made by the analyst with the same last name and same first initial;[7] (iii) the forecast and the report is for the same firm; and (iv) the date of the forecast announced and the report released date is same. I then manually double-check the matched pairs. Out of 70,274 forecasts in the forecast sample, I can link 21,346 forecasts with their corresponding analyst research reports.

4.3 Analyst Location

The matched I/B/E/S–Eikon sample includes the full name of the analysts and affiliated brokerage houses. I search the location of the analyst's working office mainly through FINRA Brokercheck by the analyst's name and her brokerage house. Brokercheck provides the historical registration information for analysts. The amazing feature of this database is that it not only provides the names of brokerage houses analysts registered but also provides the detailed geographic location information of the brokerage houses branch offices. For example, Anupam Rama (CRD = 5510790 and amaskcd = 138582) and Stephanie Yee (CRD = 5208353 and amsckd = 183351) both register under J.P. MORGAN SECURITIES LLC (CRD = 79) in 2021 June when I first downloaded this data. However, they belong to different branch offices. Anupam Rama works in San Francisco, while Stephanie Yee works in New York. These two cities went into lockdown at different times. I can identify the location information for 1,240 analysts in Brokercheck. For the rest analysts in the sample, I manually search online, e.g., LinkedIn, TipRankers, and their company websites to determine their location during the sample period. I could identify the location information for 1,340 analysts in total.

[6] If there is more than one author name for a report, the first name analyst is the leader analyst, and the rest analysts are associated analysts. The name of the analyst may include honorific titles (e.g., Dr., Mr, and Miss), education degrees (e.g., MBA), and (or) professional designation, e.g., CFA and CPA. The contributor is the brokerage house in which the analyst is affiliated.

[7] If the report is written by more than one individual analyst, the match is valid when any individual analyst's last name and first initial can be matched in both data sets.

4.4 Stay-at-Home Orders Date

Each state or territory has the authority to enact its own laws and policies to protect the public's health, and jurisdictions vary widely in the type and timing of orders issued related to stay-at-home requirements. Data on U.S. state stay-at-home orders released date are obtained from government websites containing executive or administrative orders or press releases for each jurisdiction. I double-check the date by searching the relevant median report. The announcement date of stay-at-home orders across different states is shown in Appendix Figure A1.

4.5 Main Variables and Summary Statistics

The main variable I am interested in is an indicator *Team*. For every forecast in the sample, if there is more than one author on the associated analyst research report, I treat the forecast to be made by an analyst team, and assign one to the indicator *Team*. Otherwise, the forecast is issued by an individual analyst, and the value of *Team* is zero. The other main variable is *WFH*, which represents working from home. It is also an indicator which is one if the forecast is made after the lockdown date and zero otherwise.

The main analyst performance measures I investigate in this paper are the forecast timeliness (*Timely*) and forecast accuracy (*Forecast error*). *Timely* is a dummy variable which is one if the analysts issue the forecast within one trading day after the firm's quarter earnings announcement date, and zero otherwise. Following Clement and Tse (2005), I define the forecast accuracy for firm j at time t in quarter q by analyst i in (1)

$$\text{Forecast error}_{ijt} = 100 \times \frac{|\text{Actual EPS}_{jt} - \text{Forecasted EPS}_{ijt}|}{\text{Stock price}_{jq-4}} \tag{1}$$

In other words, *Forecast error* equals the absolute value of actual company EPS minus the EPS forecast scaled by the stock's price four quarters (twelve months) prior to the quarterly earnings announcement date and multiplied by 100. It is easy to see that the higher the value is, the less accurate the forecast is.

Table 2 Panel A reports summary statistics for the main variables used in this paper. In my sample, about 57% of forecasts are issued by team analysts. This number is much larger than that provided by I/B/E/S. For example, Brown and Hugon (2009) indirectly infer the presence of analyst teams from the incidence of multiple names associated with one single analyst ID (amaskcd) in I/B/E/S. However, fewer than 6% of observations in their sample are identified as analyst teams. The fraction of team analysts in the whole industry in my sample is close to Fang and Hope (2021). I apply a similar method following their study to identify the analyst teams and find a similar proportion of analyst teams (Fang and Hope (2021) find that 70% of analysts are analyst teams in their sample). The difference may be from the different sample periods and the focus of the different analyst activities. Fang and Hope (2021) keep the last forecast issued by the analyst in each quarter over 2013 to 2016 period to gauge the forecast accuracy, while I only include the first forecast after the earnings announcement to measure the forecast timeliness in the first three quarters of 2020. Similar results in the analyst teams identification show the reliability of the analyst team identification method in this paper. The average value of *WFH* is about 69%, meaning that around 69% forecasts are issued after the stay-at-home order. This figure makes sense since most U.S. states announced the stay-at-home order around late March and the beginning of April. I choose the first three quarters in 2020, a short sample window, as the sample period to eliminate the compounding effect of other factors that could also affect the performance of the team and individual analysts. On average, analysts can issue 77% timely forecasts, which is consistent with other studies (e.g., Driskill et al. (2020)). The average forecast error is 0.80, similar to those in previous literature. Statistics from the analyst level show that, on average, one individual (team) analyst follows about 18.38 firms and 3.85 two-digit SIC industries each quarter, works for a brokerage house with around 74 analysts, has general working experience 14.73 years, and follows the firm for 5.82 years.

Table 2 Panel B reports summary statistics by states. New York State is the state with the highest number of analysts and forecasts in my sample (about 64% of all forecasts and around 67% of all analysts), which is not surprising because Wall Street is located in New York City, New York. Famous brokerage houses in my sample, e.g., JP Morgan, Morgan Stanley, and Credit Suisse are located in New York. One thing that should be noted is that brokerage houses may have multiple branches located in different cities. For example, JP Morgan has four different branch offices in my sample, which include New York (New York State), San Francisco (California State), Carrollton (Texas State), and Lake Forest (Illinois State). The detailed data from Brokercheck FINRA helps me precisely retrieve analysts' location at the branch offices level. California is ranked second with respect to the number of forecasts and number of analysts in my sample, although these figures are much smaller than those for New York State (about 10% of all forecasts and about 10% of all analysts). Other twenty-two states only account for a small fraction of the whole sample. Except for New York and California, no other states have more than 1,000 forecasts or 100 analysts. I also list the stay-at-home order announcement date for each sample state in the last column of Panel B Table 1. The first state to announce the stay-at-home order is California, which is on 19 March 2020. New York state announced the order relatively earlier (22 March 2020). The last state in my sample announcing the order is Missouri (6 April 2020).

Table 3 Panel A compares the differences between individual analysts and team analysts in the main variables in the sample. t-value is the t-test on the equality of the mean of individual and team groups. Team analysts and individual analysts behave differently with respect to forecast timeliness and forecast quality. On average, analyst teams in the sample period can issue more timely forecasts (78% v.s. 74%), and the difference is statistically significant ($t-$value is -5.68). Individual analysts' forecast error is larger (0.83 v.s. 0.77) and significant compared to team analysts. This finding is inconsistent with the previous literature that teams are less accurate than individual analysts (Brown and Hugon (2009)). It provides descriptive evidence on my hypothesis that teams improve their forecast quality during crisis working from home periods since about 70% of forecasts are issued during the COVID-19 pandemic. I will show more evidence on this argument in the following analyses. I turn to other analysts and firm characteristics and find that the difference between individual and team analysts for some variables are significantly different, and the differences are economically large. For example, individual analysts are on average from smaller brokerage houses while analyst teams are from larger brokerage houses. The large difference that appears in *Team size* is due to the definition of the variable. There are statistically significant between teams and individual analysts in some dimensions, but the magnitudes are not large. On average, analyst teams in the sample period can cover more firms (18.60 v.s. 18.09), have more general and firm experience. It shows that team analysts always issue more timely forecasts compared to individual analysts. In my main analysis, I carefully control these variables that could potentially affect forecast timeliness.

Next, I focus on the analyst teams and check whether there are any differences among analyst teams of different sizes. Table 3 Panel B reports the comparison within teams. I classify the analyst teams into four different categories according to team size: two members, three members, four members, and more than four members. The first row reports the proportions of each team size group in the sample. Teams with two members account for about 42% team observations in the sample. Three-member teams are about 34% in the team sample. A team with at least five members only consists of about 6% sample. Considering the sample size of different team size categories, I check the heterogeneity of teams by comparing the two-member teams with other teams categories. Column (5) reports the difference between two-member teams and other teams across different variables, and the last column reports the t-statistics of the t-tests on the equality of mean for two groups. For the performance measures I am interested in this paper, I find some heterogeneity among teams with different team sizes. The likelihood of issuing timely forecasts for teams with different members is similar. The largest teams could issue the most timely forecasts. I also find a U-shape relationship between team size and forecast error. Teams with middle size (three) can issue the most accurate forecasts, while those smallest and largest teams (two and above five) have the least accurate forecasts. The difference between the two-member teams and other teams is statistically insignificant for other variables, and the magnitude is relatively small. The modest difference is on forecast frequency: the larger the size is, the more forecasts are. Smaller firms have more general analyst industry experience while they have less firm specific experience. On average, smaller teams covered fewer firms and industries, which makes sense.

5 Empirical Strategy and Results

5.1 Empirical Strategy

This paper takes advantage of staggered introduced stay-at-home policy in U.S. states during the COVID-19 pandemic in 2020 as a quasi-natural experiment to investigate how working from home policy during the COVID-19 pandemic affects the team and individual analysts differently. I apply the difference-in-differences (DID) method in the main empirical analysis to compare analysts' performance during the COVID-19 pandemic in team analysts and individual analysts. I estimate the following model:

$$Performance_{ijqt} = \alpha + \beta Team_i \times WFH_{ijqt} + \gamma WFH_{ijqt} + \mathbf{X}'_{ijqt}\delta + \mu_{jq} + \vartheta_{ij} + \theta_t + \varepsilon_{ijqt} \quad (2)$$

where i indexes analysts, j indexes firms, q indexes fiscal quarters, and t indexes calender months. $Performance_{ijqt}$ includes two analysts' performance measures, $Timely_{ijqt}$ and $\textit{Forecast error}_{ijqt}$ which are defined above. $Team_i$ is a dummy variable which is one if the forecast is issued by more than one analyst and zero otherwise, and WFH_{ijqt} is an indicator which is one if the forecast for firm j by analyst(s) i at time t is issued after the state stay-at-home policy and zero otherwise. Control variables $\mathbf{X}_{ijqt}$ include analyst and brokerage characteristics.

I include *Firm* $\times$ *Fiscal Quarter* fixed effects μ_{jq} in all specifications. By including *Firm* $\times$ *Fiscal Quarter* fixed effects in the regression model, I compare the forecast timeliness likelihood between team analysts and individual analysts by requiring them to do the same tasks: making forecasts for the same firm's earnings of the same fiscal quarter. It also explains why I do not include fiscal quarter firm characteristics in control variables $\mathbf{X}_{ijqt}$ of the model (2): the fiscal end firm characteristics are absorbed by the *Firm* $\times$ *Fiscal Quarter* fixed effects. In the most stringent specification I include *Analyst* $\times$ *Firm* fixed effects ϑ_{ij} and *Year-month* fixed effects θ_t in the model. *Analyst* $\times$ *Firm* fixed effects absorb the variable *Team*. Since most states in my sample do not announce the stay-at-home order on the first day of a month, a forecast issued in March or April could be before or after the stay-at-home order. Therefore, the variable *WFH* is not fully absorbed by the year-month time fixed effects. The standard errors are clustered at the analysts and firms level.

5.2 WFH and Team Performance

Table 4 reports the results of regression model (2). Columns (1) to (3) present results with *Timely* as the dependent variable, which captures the likelihood of issuing a timely forecast. I include different sets of fixed effects for different specifications. In column (1) I include the *Analyst* and *Firm* $\times$ *Fiscal Quarter* fixed effects. The estimated coefficients of *WFH* are negative but not significant. The coefficient for the interaction *WFH*$\times$*Team*, which I am interested, is positive and significant at the 1% level. The magnitude of interaction term indicates that team analysts' forecast timeliness is about 4.1% higher than that of individual analysts after the stay-at-home order. In column (2) I include the *Analyst*, *Year-month time*, and *Firm* $\times$ *Fiscal Quarter* fixed effects. The estimated coefficient on *WFH* becomes statistically significant at the 5% level. The estimated coefficient on the interaction term *WFH* $\times$ *Team* decreases to 3.8% and is still statistically significant at the 1% level. The magnitude is economically meaningful given the mean of forecast timeliness, 77% (about 5.0% in relative to the mean level). In the last specification in (3), I run a very strict model by including the *Year-month*, *Analyst* $\times$ *Firm*, *Firm* $\times$ *Fiscal Quarter* fixed effects. This model can effectively compare within analyst forecasts after the same firm's same earnings announcement. I still find a significantly positive coefficient for *WFH* at the 10% level in this specification. The magnitude (-0.071) is similar to those in columns (1) and (2). The estimated coefficient on *WFH* $\times$ *Team* (0.037) is still positive and significant at the 5% level, which suggests that team analysts' timeliness forecasts likelihood is about 3.7% higher than that of individual analysts after the stay-at-home order within the same firm-quarter. The magnitude is slightly smaller than those in the previous specifications but still economically meaningful. The findings for analyst forecast timeliness reported in the first three columns of Table 4 provide strong, significant, and consistent evidence that working from home caused by the COVID-19 stay-at-home order largerly and negatively affect the forecast timeliness likelihood, which supports hypothesis **H1**. More importantly, the effect is more pronounced for individual analysts. Compared to individual analysts, team analysts have a higher probability of issuing timely forecasts after the stay-at-home order, which supports hypothesis **H2**.

Next, I move to the forecast error results reported in columns (4) to (6). The estimated coefficients on *WFH* are all positive except for that in column (6), the strictest specification. The magnitude is large. After working from home, analysts' forecast error increases by about 0.48, which is meaningful compared to the average forecast error of about 0.8. This result supports hypothesis **H1**. However, the estimated coefficients on the interaction term *Team* $\times$ *WHF* are all not significant even at the 10% level across three specifications. This result indicates that team analysts do not performe worse compared to individual analysts in terms of issuing accurate forecasts after the COVID-19 working from home policy. As noted above, previous studies find mixed results on the difference of forecast accuracy between individual and team analysts, my results provide new evidence that team analysts and individual analysts can produce forecasts with similar accuracy during crisis periods.

5.3 Dynamic Effects

I next investigate the dynamic effect of working from home on analyst forecast timeliness and accuracy difference between team and individual analysts. To do so, I extend the sample period to the third quarter of 2019 and split the extended sample period into five subperiods: the third quarter in 2019 (2019Q3), the fourth quarter in 2019 (2019Q4), the first quarter in 2020 (2020Q1), the second quarter in 2020 (2020Q2), and the third quarter in 2020 (2020Q3). Then I interact these five subperiods dummy variables with the dummy variable *Team* and run a similar regression as that in regression model (2). The regression specification is shown as follows:

$$
\begin{aligned}
Performance_{ijqt} \quad = \quad & \alpha + \beta_1 Team_i \times 2019Q3_{ijqt} + \beta_2 Team_i \times 2019Q4_{ijqt} \\
& + \beta_3 Team_i \times 2020Q1_{ijqt} + \beta_3 Team_i \times 2020Q2_{ijqt} \\
& + \beta_4 Team_i \times 2020Q3_{ijqt} \\
& + \mathbf{X}'_{ijqt}\delta + \mu_{jq} + \vartheta_{ij} + \theta_t + \varepsilon_{ijqt}
\end{aligned} \tag{3}
$$

where $2019Q3_{ijqt}$ is a dummy variable which takes value one if time t when analyst i's earnings forecast for firm j in quarter q is made is in the third quarter of 2019 and zero otherwise. Other time dummy variables, $2019Q4_{ijqt}$, $2020Q1_{ijqt}$, $2020Q2_{ijqt}$, and $2020Q3_{ijqt}$ are defined similarly. One remark is that since the stay-at-home policy in my sample was implemented between 19 March 2020 and 6 April 2020 in different states, it is possible that some forecasts were issued in the first quarter of 2020 but after the stay-at-home order and some were made in the second quarter of 2020 but before the stay-at-home order in that state. To get a clean result, I drop those observations. All other variables are same as those in the baseline model (2).

I report the regression results in Table 5. The first three specifications, including sets of different fixed effects, provide similar results with respect to forecast timeliness. The effect of working from home policy on forecast timeliness likelihood differences between team and individual analysts is concentrated on the second quarter of 2020. That is, the effect exists only in the period after the announcement of stay-at-home order. The team and the individual difference before the stay-at-home order is very weak and not significant, indicating that individual and team analysts could issue similarly timely forecasts before the COVID-19 pandemic normal period. The estimated coefficients on *Team* × *2020Q3* are positive but not significant across all first columns. It indicates that the effect of working from home on the team-individual difference in forecast timeliness seems to decay with time. One possible explanation consistent with this finding is that team and individual analysts get used to the new working style. There are two main takeaways of this dynamic effect test. First, it provides additional evidence that working from home policy does affect the forecast timeliness likelihood differently between team and individual analysts. Second, the effect only exists after the event which is evident in the parallel trend assumption of DID.

Next, I discuss the working from home dynamics effect results on forecast accuracy reported in columns (4) to (6). There are some interesting findings. First, the estimated coefficients on *Team* × *2020Q1* are all significantly positive, indicating that analyst teams perform worse before the COVID-19 pandemic during the normal time. It is consistent with the previous finding that teams are less accurate than individual analysts in earnings forecasts (Brown and Hugon (2009)). Second, teams' forecasts become more and more accurate during the COVID-19 pandemic working from home period. No difference in forecast accuracy between teams and individual is found in the second quarter of 2020, the first quarter of working from home policy. I find positive and significant estimated coefficients on *Team* × *2020Q3*, indicating that teams perform better compared to individuals in the third quarter of 2020. The dynamic results on forecast errors supplement the findings in the baseline analysis. Although no difference of forecast accuracy is found between teams and individuals during the entire working from home period, teams' forecasts become more and more accurate over time compared to individuals.

5.4 Team Size Effect

As discussed in the related literature section, team size plays a crucial role in teams' performance. I expect that the larger team size leads to the higher likelihood of issuing a timely forecast. To formally test this hypothesis, I run a similar regression specification as regression model 2 except that I now replace the dummy variable *Team* by the number of team members, i.e., the team size *Team size*. By definition, the team size is one for individual analysts. I report the results in Table 6. From columns (1) to (3), I find that the estimated coefficients for the interaction term *Team size* × *WFH* are all positive and significant. Take the first column result as an example to discuss the economic interpretation. The estimated coefficient for the interaction term *Team size* × *WFH* is 0.02 and significant at the 1% level, meaning one additional member added to the analyst team increases the likelihood of issuing a timely forecast by about 2% after working from home when keeping other variables constant. This effect is economically meaningful. The largest teams in my sample contain five analysts. The results found in Table 6 indicate that they are about 8% higher to issue timely forecasts compared to individual analysts after the pandemic. A question arising from this result is whether an optimal team size exists. I, therefore, add a quadratic term *team size*^{2} in the regression specification. However, I no longer find significant results in columns (4)–(6). It suggests that no optimal team size exists in my sample and setting for analysts to make timely forecasts. The benefits of adding more team members exceed the costs of larger teams, such as coordination costs. During working from home periods, although analysts could be distracted, the probability that all members are distracted is lower for larger teams compared to smaller teams and individual analysts. Therefore, they could issue more timely forecasts. The results are evident to the hypothesis **H3a**.

For forecast accuracy, I posit that an optimal team size that trades off the benefits and costs of a larger team size exists. Columns (7) to (12) of Table 6 report the results. The estimated coefficients on *Team size* $\times$ *WFH* are positive but not statistically significant even at the 10% level across all specifications, indicating that in contrast to forecast timeliness, increasing the team size cannot improve the forecast accuracy. Interestingly I find consistently and significantly positive estimated coefficients on *Team size*^{2} $\times$ *WFH* in columns (10) to (12) with different sets of fixed effects. These results imply that a U-shaped relationship between team size and forecast accuracy exists. That is, there is an optimal team size that can maximize the forecast accuracy during tough times. Using the estimated results in the last column to illustrate. When the team size is 2.29 ($0.055/(2 \times 0.012)$), this team can issue the most accurate forecasts compared to individual analysts in the post COVID-19 pandemic period. It is consistent with the finding of univariate analysis in Table 3 Panel B. My findings here support hypothesis **H3b**.

6 Additional Analyses

6.1 Robustness Check

Previous studies show that analysts' forecasts experience the seasonality (Lo and Wu (2018); Chang et al. (2017)). To mitigate this concern, I use the period from March 19th, 2019 to August 31st, 2019 as the control group and compare it with the same period in 2020. The choice of the starting day March 19th is that it is the day when the first U.S. state, California, announced the stay-at-home order. Almost all forecasts between March 19th to August 31st, 2020 can be assumed to be made after working from home policies. The forecasts in 2019 are issued in the normal working environment, which could be treated as the control group. In this setting, *WFH* is one if a forecast is made in 2020 and zero otherwise. I repeat the analysis in Table 4 and report the results in Table 7. In this setting variable *WFH* is absorbed when including *Year-month* fixed effects in the regression model. For brevity, I only report the estimated results of the interaction term *WFH* $\times$ *Team*. The estimated coefficients for *WFH* $\times$ *Team* are significantly positive, at least at 5%. The magnitudes are larger than those in the baseline analysis, especially for the strictest specification. The magnitude of coefficients in columns (3) and (6) is double that in the baseline analysis. The results in robust tests confirm the findings in the baseline analysis: individual analysts are affected more compared to team analysts by the working from home policy with respect to the forecast timeliness likelihood.

6.2 Team Analysts and Market Efficiency

The results discussed above show that team analysts can issue more timely forecasts than individual analysts after implementing the working from home policy caused by the outbreak of the COVID-19 pandemic. Meanwhile, I find no significant difference in forecast accuracy between individual and team analysts after working from home. It is an interesting and important question whether team analysts can improve market efficiency if they only provide timely but not so accurate forecasts. Or, in the other way around, how bad are those late forecasts made by individual analysts to the market efficiency. I answer this question from two aspects.

Firstly, I examine whether teams issue forecasts much earlier than individual analysts. In other words, how many days are teams earlier than individuals? My above analyses only use a dummy variable *Timely*, but now I use a continuous forecast timeliness measure *Delay*, which is defined as the number of days elapsed from the earnings announcement date until the first forecast of annual earnings (Mayew et al. (2013)). The smaller *Delay*, the more timely the forecast. I repeat the analysis in baseline but replace the indicator *Timely* with the continuous timeliness measure *Delay*. The results are reported in Table 8. I do not find any significant results on the interaction term $Team \times WFH$ or WFH no matter the raw delay or the natural logarithm of delay is examined. The sign of estimated coefficients on $Team \times WFH$ and WFH is consistent with the findings in the baseline, but the coefficients are not significant. The results suggest that teams and individual analysts can issue similarly timely forecasts.

Secondly, since I find that although teams can issue more timely forecasts, the absolute day gap between team and individual analysts is very small according to the results found in Table 8. Meanwhile, I find that teams and individual analysts can issue almost equally accurate forecasts during COVID-19 working from home period. These findings suggest that team analysts cannot improve market efficiency, although they, on average, can issue more timely forecasts. In this section, I investigate the market reaction to check whether the market reacts more to forecasts made by teams after working from home policy. Suppose investors' reaction to forecasts made by teams is larger than those made by an individual during the working from home period. In that case, it means that investors care more about teams' forecasts during tough times. They believe that team analysts' forecasts are more informative and could improve market efficiency.

I follow the standard way used in accounting literature and relate the cumulative abnormal stock returns around the day the analysts release their forecasts on whether the forecasts are released by teams or individual analysts and on whether the forecasts are issued during working from home time (Bradshaw et al. (2017b); Gibbons et al. (2021)). The results are reported in Table 9, where *CAR[0,+1]* is the two-day cumulative abnormal returns around analyst's forecast for a certain firm. The cumulative abnormal returns are estimated based on a market model. The key findings are as follows. Firstly, in all columns, I find that the market reactions measured by CAR are higher when the forecasts are issued during the working from home period, although the estimated coefficients on *WFH* are not significant. More importantly, the estimated coefficients on interaction term *Team* × *WFH* are significantly positive at least at the 5% level except in all three columns. CARs are on average 0.1%–0.2% larger for forecasts if they are issued by team analysts compared to individual analysts during the working from home period. The magnitude is meaningful considering the mean of $CAR[0,+1]$ is roughly 0.2%.

Overall, the results on the market reaction test show that although teams issue only a little earlier forecasts compared to individual analysts, the investors are aware that forecasts made by team analysts are more informative compared to those made by individual analysts during the pandemic time.

6.3 Other Analysts Activities

The analyses above focus on forecast timeliness and accuracy, the most important two perspectives to measure the performance of analysts. In addition to these two measures, I examine whether analyst teams can perform better than individual analysts after stay-at-home order on other analysts quality dimensions: forecast update and the length of the analyst research reports. The forecast update *Forecast update* is measured as the number of forecasts revisions the analysts make for a firm in a certain quarter. If analysts think that their initial forecasts are accurate, they are less likely to update their initial forecasts even new information arrives. Therefore, I expect that team analysts update forecasts less compared to individual analysts after working from home. The length of the analyst research reports *Log(1+Num page)* is measured by the natural logarithm of one plus the number of pages of the associated research report for the first forecast issued after the earnings announcement. Writing reports is time-consuming and grabs analysts' attention, especially during the pandemic working from home period. Team analysts, on average, are less likely to be distracted compared to individual analysts. So I posit that team analysts can write more reports than individual analysts during working from home time.

I repeat the DID regression model in the baseline analysis but replace the forecast timeliness measure with the other three forecast activities measures. The results are reported in Table 10. Columns (1) to (3) show that the effect of working from home team on forecast updating is larger for team analysts than that of individual analysts. Team analysts, on average, issue 0.11–0.14 fewer forecasts revision compared to individual analysts after the stay-at-home order. It supports my expectation that team analysts may believe their first forecasts are accurate and do not update them often compared to individual analysts. Columns (4) to (5) show evidence that team analysts, on average, write about 3.8%–4% more pages compared to individual analysts after working from home. This is evident in the argument that individual analysts are more distracted when working from home compared to team analysts. The results provide further evidence that analyst teams outperform individual analysts during tough times when the tasks need more attention and time.

7 Conclusion

Teams are common in business organizations nowadays. Previous studies mostly compare the performance difference between teams and individuals during normal times. In this paper I use the financial analyst teams as the laboratory and exploit the exogenous introduced stay-at-home order during the COVID-19 pandemic to investigate whether analyst teams can perform better compared to individual analysts in crisis periods. This unique setting assumes that the team composition is predetermined and exogenous to the unexpected COVID-19 pandemic shock and allows me to compare differences in responses between team and individual analysts. Applying the difference-in-differences method on a sample of forecasts issued by team and individual analysts in the first three quarters of 2020, I find that after the stay-at-home orders, both teams and individual analysts perform worse during working from home period in terms of less timely and accurate forecasts. However, on average, teams perform better than individual analysts do. Team analysts can issue more timely forecasts than individual analysts without losing forecast accuracy. In addition, team size plays an important role in teams' performance. There exists a monotonic positive relation between team size and analyst forecast timeliness and a U-shaped relationship between team size and forecast accuracy. A further test shows that investors react more to teams' forecasts issued during the pandemic than individual's forecasts. In summary, my results indicate that teams perform better than individuals during tough times.

References

Adams, John C, Takeshi Nishikawa, and Ramesh P Rao, 2018, Mutual fund performance, management teams, and boards, *Journal of Banking and Finance* 92, 358–368.

Ahern, Kenneth R, and Amy K Dittmar, 2012, The changing of the boards: The impact on firm valuation of mandated female board representation, *Quarterly Journal of Economics* 127, 137–197.

Auerswald, Heike, Carsten Schmidt, Marcel Thum, and Gaute Torsvik, 2018, Teams in a public goods experiment with punishment, *Journal of Behavioral and Experimental Economics* 72, 28–39.

Bär, Michaela, Alexander Kempf, and Stefan Ruenzi, 2011, Is a team different from the sum of its parts? Evidence from mutual fund managers, *Review of Finance* 15, 359–396.

Barrero, Jose Maria, Nicholas Bloom, and Steven J Davis, 2021, Why working from home will stick, NBER Working paper.

Becker, Gary S, and Kevin M Murphy, 1992, The division of labor, coordination costs, and knowledge, *Quarterly Journal of Economics* 107, 1137–1160.

Bernile, Gennaro, Vineet Bhagwat, and Scott Yonker, 2018, Board diversity, firm risk, and corporate policies, *Journal of Financial Economics* 127, 588–612.

Bick, Alexander, Adam Blandin, and Karel Mertens, 2020, Work from home after the COVID-19 outbreak, *CEPR Discussion Paper No. DP15000* .

Bloom, Nicholas, James Liang, John Roberts, and Zhichun Jenny Ying, 2015, Does working from home work? Evidence from a chinese experiment, *Quarterly Journal of Economics* 130, 165–218.

Bolisani, Ettore, Enrico Scarso, Christine Ipsen, Kathrin Kirchner, and John Paulin Hansen, 2020, Working from home during COVID-19 pandemic: lessons learned and issues, *Management & Marketing. Challenges for the Knowledge Society* 15, 458–476.

Boning, Brent, Casey Ichniowski, and Kathryn Shaw, 2007, Opportunity counts: Teams and the effectiveness of production incentives, *Journal of Labor Economics* 25, 613–650.

Bradshaw, Mark T, Yonca Ertimur, and Patricia C O'Brien, 2017a, Financial analysts and their contribution to well-functioning capital markets .

Bradshaw, Mark T, X Wang, and D Zhou, 2017b, Soft information in the financial press and analysts' recommendation revisions, Working paper.

Brown, Lawrence D, and Artur Hugon, 2009, Team earnings forecasting, *Review of Accounting Studies* 14, 587–607.

Brynjolfsson, Erik, John J Horton, Adam Ozimek, Daniel Rock, Garima Sharma, and Hong-Yi TuYe, 2020, COVID-19 and remote work: An early look at us data, NBER Working paper.

Chang, Tom Y, Samuel M Hartzmark, David H Solomon, and Eugene F Soltes, 2017, Being surprised by the unsurprising: Earnings seasonality and stock returns, *Review of Financial Studies* 30, 281–323.

Chen, Jean Jinghan, Li Xie, and Si Zhou, 2020, Managerial multi-tasking, team diversity, and mutual fund performance, *Journal of Corporate Finance* 65, 101766.

Cheng, Shijun, 2008, Board size and the variability of corporate performance, *Journal of Financial Economics* 87, 157–176.

Chiu, Peng-Chia, Ben Lourie, Alexander Nekrasov, and Siew Hong Teoh, 2021, Cater to thy client: Analyst responsiveness to institutional investor attention, *Management Science* 67, 7455–7471.

Clement, Michael B, and Senyo Y Tse, 2005, Financial analyst characteristics and herding behavior in forecasting, *Journal of Finance* 60, 307–341.

Cooper, David J., and John H. Kagel, 2005, Are two heads better than one? Team versus individual play in signaling games, *American Economic Review* 95, 477–509.

Cooper, Rick A, Theodore E Day, and Craig M Lewis, 2001, Following the leader: A study of individual analysts' earnings forecasts, *Journal of Financial Economics* 61, 383–416.

DeHaan, Ed, Terry Shevlin, and Jacob Thornock, 2015, Market (in) attention and the strategic scheduling and timing of earnings announcements, *Journal of Accounting and Economics* 60, 36–55.

Delfgaauw, Josse, Robert Dur, Oke Onemu, and Joeri Sol, 2022, Team incentives, social cohesion, and performance: A natural field experiment, *Management Science* 68, 230–256.

Driskill, Matthew, Marcus P Kirk, and Jennifer Wu Tucker, 2020, Concurrent earnings announcements and analysts' information production, *The Accounting Review* 95, 165–189.

Du, M, 2020, Locked-in at home: Female analysts' attention at work during the COVID-19 pandemic, Working paper, University of Mannheim.

Dutcher, E Glenn, 2012, The effects of telecommuting on productivity: An experimental examination. the role of dull and creative tasks, *Journal of Economic Behavior and Organization* 84, 355–363.

Fang, Bingxu, and Ole-Kristian Hope, 2021, Analyst teams, *Review of Accounting Studies* 26, 425–467.

Gao, Menghai, Yuan Ji, and Oded Rozenbaum, 2021, When do associate analysts matter?, *Management Science* .

Gibbons, Brian, Peter Iliev, and Jonathan Kalodimos, 2021, Analyst information acquisition via EDGAR, *Management Science* 67, 769–793.

Graham, John R, Campbell R Harvey, and Manju Puri, 2015, Capital allocation and delegation of decision-making authority within firms, *Journal of Financial Economics* 115, 449–470.

Groysberg, B., and P. Healy, 2013, *Wall Street Research: Past, Present, and Future* (Stanford University Press).

Hamilton, Barton H, Jack A Nickerson, and Hideo Owan, 2003, Team incentives and worker heterogeneity: An empirical analysis of the impact of teams on productivity and participation, *Journal of Political Economy* 111, 465–497.

Kniffin, Kevin M, Jayanth Narayanan, Frederik Anseel, John Antonakis, Susan P Ashford, Arnold B Bakker, Peter Bamberger, Hari Bapuji, Devasheesh P Bhave, Virginia K Choi, et al., 2021, COVID-19 and the workplace: Implications, issues, and insights for future research and action, *American Psychologist* 76, 63.

Li, Frank Weikai, and Baolian Wang, 2021, The gender effects of COVID-19 on equity analysts, Working paper, Singapore Management University.

Lo, Kin, and Serena Shuo Wu, 2018, The impact of seasonal affective disorder on financial analysts, *The Accounting Review* 93, 309–333.

Luo, Jiang, and Zheng Qiao, 2020, Individual commitment and team performance: Evidence from mutual fund managers, *Journal of Financial and Quantitative Analysis* 55, 2073–2098.

Mateyka, Peter J, Melanie Rapino, and Liana Christin Landivar, 2012, *Home-based workers in the United States: 2010* (US Department of Commerce, Economics and Statistics Administration, US Census Bureau).

Mayew, William J, Nathan Y Sharp, and Mohan Venkatachalam, 2013, Using earnings conference calls to identify analysts with superior private information, *Review of Accounting Studies* 18, 386–413.

Moreland, Amanda, Christine Herlihy, Michael A Tynan, Gregory Sunshine, Russell F McCord, Charity Hilton, Jason Poovey, Angela K Werner, Christopher D Jones, Erika B Fulmer, et al., 2020, Timing of state and territorial COVID-19 stay-at-home orders and changes in population movement–United States, March 1-May 31, 2020, *Morbidity and Mortality Weekly Report* 69, 1198.

Mueller, Jennifer S, 2012, Why individuals in larger teams perform worse, *Organizational Behavior and Human Decision Processes* 117, 111–124.

Patel, Saurin, and Sergei Sarkissian, 2017, To group or not to group? evidence from mutual fund databases, *Journal of Financial and Quantitative Analysis* 52, 1989–2021.

Ramarajan, Lakshmi, and Erin Reid, 2013, Shattering the myth of separate worlds: Negotiating nonwork identities at work, *Academy of Management Review* 38, 621–644.

Ruktanonchai, Nick Warren, JR Floyd, Shengjie Lai, Corrine Warren Ruktanonchai, Adam Sadilek, Pedro Rente-Lourenco, Xue Ben, Alessandra Carioli, Joshua Gwinn, JE Steele, et al., 2020, Assessing the impact of coordinated COVID-19 exit strategies across europe, *Science* 369, 1465–1470.

Zhang, Yuan, 2008, Analyst responsiveness and the post-earnings-announcement drift, *Journal of Accounting and Economics* 46, 201–215.

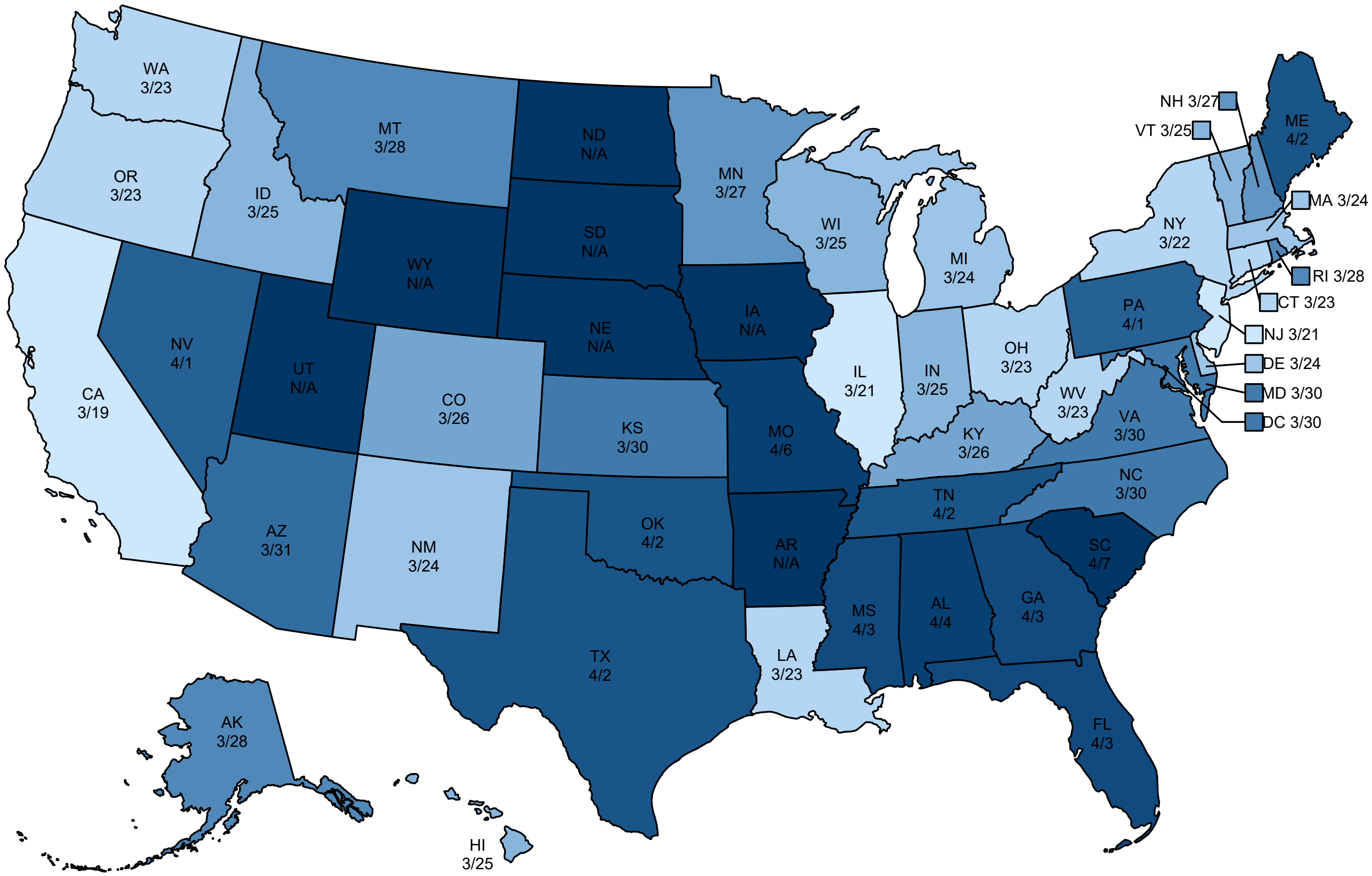

Figure 1: Announcement Date of Stay-at-home Orders across U.S. States

This figure plots announcement dates of stay-at-home orders of U.S. states. The date with the format “month/day” is shown below state codes. If a state does not announce a stay-at-home order, the date is “N/A”. The darker the color, the later the state announces the order.

Table 1: Sample Construction

This table reports the sample construction procedure for the empirical analyses.

	# Firms	# Forecasts	# Analysts	# Team Members
Obtain all analysts' quarter EPS forecasts over the first three quarters in 2020 from I/B/E/S Actuals and Details database.	4,339	126,796	2,715	
Keep forecasts with earnings announcement date and quarter end gap no more than 90 days.	4,320	125,726	2,707	
Merge with CRSP and drop observations in which fiscal quarter stock price smaller than 1$.	3,716	116,611	2,374	
Keep observations in which the forecast date is at least one day prior to the earnings announcement date.	3,715	115,782	2,371	
Merge with I/B/E/S Recommendation database to retrieve the name of analyst. Drop observations made by research departments or more than one analyst sharing the same analyst ID (amaskcd).	3,710	115,454	2,283	
Keep the first forecast made after the earnings announcement.	3,685	70,325	2,272	
Merge forecasts observations with Eikon to obtain the full name all authors from analyst research reports.	2,878	21,559	1,207	2,058
Search each author's location information using her full name and brokerage house name through FINRA and other online sources.	2,832	20,544	1,096	1,882
Final clean: (i) drop if earnings announcement occurring before stay-at-home orders and forecasts issued after orders; (ii) drop states without stay-at-home orders; (iii) drop firms only covered by team or individual.	1,475	12,249	1,301	1,653

Table 2: Summary Statistics

This table reports summary statistics for a sample of the first forecast issued by analysts for a firm's earnings in next quarter after firm's earnings announcement in the sample period of January–August 2020. Panel A presents summary statistics for the main variables in this paper. Panel B reports the number of observations by states and their corresponding stay-at-home order announcement date. States are ranked in descending order according to the number of analysts located in each state. All variables are defined in the Appendix A1. All continuous variables are winsorized at 1% level.

Panel A: Summary Statistics for Main Variables

	N	Mean	SD	Min	Median	Max
Team	12,249	0.57	0.50	0.00	1.00	1.00
WFH	12,249	0.69	0.46	0.00	1.00	1.00
Timely	12,249	0.77	0.42	0.00	1.00	1.00
Forecast error	12,008	0.80	1.29	0.00	0.33	6.85
Forecast update	12,249	1.71	0.80	1.00	2.00	4.00
Num page	12,085	20.64	14.01	6.00	17.00	103.00
Team size	12,249	2.06	1.15	1.00	2.00	5.00
Female leader	12,249	0.09	0.29	0.00	0.00	1.00
Diversity	6,840	0.43	0.12	0.25	0.44	0.70
Num firm covered	12,249	18.38	7.16	3.00	18.00	37.00
Num ind covered	12,242	3.85	2.42	1.00	3.00	10.00
General exp	12,249	14.73	9.04	0.37	14.48	33.95
Firm exp	12,249	5.82	5.46	0.00	4.20	22.45
Broker size	12,249	74.36	55.53	4.00	57.00	204.00

Panel B: Summary Statistics by States

State	Forecasts		Analysts		Stay-at-home
	Num	Percent	Num	Percent	Announcement Date
New York	7,846	67.18%	874	64.05%	2020-03-22
California	1,243	10.45%	136	10.15%	2020-03-19
Illinois	555	5.07%	66	4.53%	2020-03-21
Minnesota	494	3.46%	45	4.03%	2020-03-27
Texas	319	2.38%	31	2.60%	2020-04-02
Massachusetts	268	2.38%	31	2.19%	2020-03-24
Tennessee	236	1.31%	17	1.93%	2020-04-02
Connecticut	205	1.38%	18	1.67%	2020-03-23
Florida	188	1.23%	16	1.53%	2020-04-03
Ohio	177	0.69%	9	1.45%	2020-03-23
Missouri	128	0.69%	9	1.04%	2020-04-06
Georgia	119	0.61%	8	0.97%	2020-04-03
Virginia	99	0.38%	5	0.81%	2020-03-30
Pennsylvania	90	0.77%	10	0.73%	2020-04-01
Oregon	87	0.54%	7	0.71%	2020-03-23
Maine	66	0.23%	3	0.54%	2020-04-02
New Jersey	48	0.31%	4	0.39%	2020-03-21
Maryland	34	0.31%	4	0.28%	2020-03-30
Colorado	11	0.23%	3	0.09%	2020-03-26
Washington	11	0.08%	1	0.09%	2020-03-23
North Carolina	9	0.08%	1	0.07%	2020-03-30
Nevada	7	0.08%	1	0.06%	2020-04-01
Kansas	5	0.08%	1	0.04%	2020-03-30
Wisconsin	4	0.08%	1	0.03%	2020-03-25
All	12,249	100.00%	1,301	100.00%	

Table 3: Comparison between Team and Individual Analysts and within Team Analysts

This table reports the differences of main variables between team and individual analysts and within team analysts with different team sizes in the sample period of January–August 2020. Panel A reports the differences of main variables between team analysts and individual analysts. An analyst in I/B/E/S is classified as a team analyst if the associated research report for the forecast has more than one authors and otherwise she is classified as an individual analyst. Columns (1) to (2) report the number of observations and mean of main variables for the individual analysts sample and columns (3) to (4) reports the corresponding statistics for the team analyst sample. Column (5) shows the differences in mean of variables between individual and team analysts sample. The last column reports the t-statistics of the t-test on the equality of means of two subsamples. Panel B reports the mean of main variables of analyst teams with different team sizes. The sample only include the team analysts sample. Teams are classified into four categories according to the team size: two members, three members, four members, and more than four members. The fraction of each team category is reported within the parentheses. Columns (1) to (3) reports the mean of main variables for analyst teams with size two, three, and four. Column (4) reports the mean of main variables for analyst teams with at least five members. Column (5) shows the difference in mean of variables between teams with size two and teams with size more than two. The last column reports the t-statistics of the t-test on the equality of means of team with size two and team with size more than two. All variables are defined in the Appendix A1. All continuous variables are winsorized at 1% level.

Panel A: Difference between Team and Individual Analysts

	(1)	(2)	(3)	(4)	(5)	(6)
	Individual Analyst		Team Analyst		(2) − (4)	
	N	Mean	N	Mean	Difference	t-value
Team	5,282	0.00	6,967	1.00	-1.00	
WFH	5,282	0.68	6,967	0.69	-0.01	-1.24
Timely	5,282	0.74	6,967	0.78	-0.04	-5.68
Forecast error	5,175	0.83	6,833	0.77	0.06	2.58
Forecast update	5,282	1.64	6,967	1.76	-0.12	-7.91
Num page	5,219	18.68	6,866	22.12	-3.44	-13.47
Team size	5,282	1.00	6,967	2.87	-1.87	-150.66
Female leader	5,282	0.08	6,967	0.11	-0.03	-5.96
Diversity	5,282	0.00	6,840	0.43	-0.43	-266.15
Num firm covered	5,282	18.09	6,967	18.60	-0.52	-3.96
Num ind covered	5,280	3.81	6,962	3.89	-0.08	-1.88
General exp	5,282	14.47	6,967	14.93	-0.46	-2.82
Firm exp	5,282	5.49	6,967	6.07	-0.58	-5.87
Broker size	5,282	41.38	6,967	99.36	-57.99	-66.88

Panel B: Difference among Teams with Different Team Sizes

	(1)	(2)	(3)	(4)	(5)	(6)
	Size = 2 (42.36%)	Size = 3 (34.30%)	Size = 4 (17.61%)	Size $\geq$ 5 (5.73%)	Difference	t-value
Team	1.00	1.00	1.00	1.00	0.00	
WFH	0.71	0.67	0.69	0.66	0.03	2.49
Timely	0.79	0.79	0.76	0.82	0.00	0.47
Forecast error	0.80	0.68	0.82	0.90	0.06	1.85
Forecast update	1.66	1.79	1.87	1.90	-0.16	-8.17
Num page	20.85	21.99	24.08	26.29	-2.20	-6.07
Team size	2.00	3.00	4.00	5.00	-1.50	-121.97
Female leader	0.11	0.08	0.11	0.22	0.00	0.54
Diversity	0.40	0.43	0.47	0.52	-0.05	-19.04
Num firm covered	17.92	18.52	20.41	18.59	-1.18	-6.56
Num ind covered	3.84	3.79	4.09	4.23	-0.08	-1.37
General exp	15.60	14.21	15.62	12.29	1.15	5.38
Firm exp	5.77	6.45	6.15	5.87	-0.53	-3.91
Broker size	73.59	115.73	121.73	123.14	-44.71	-35.32

Table 4: DID Baseline Results

This table reports the results on how working from home affects team and individual analysts differently on analysts forecast performance measued by *Timely* and *Forecast error*. *Team* is an indicator which is one if a forecast's associated research report is written by more than one authors and zero otherwise. *WFH* is an indicator which is one if a forecast is made by the analyst after the stay-at-home policy in the state where the analyst is located and zero otherwise. All variables are defined in the Appendix A1. All continuous variables are winsorized at 1% level. Standard errors clustered at the firm level and the analyst level. *t*-statistics are reported within parentheses under the estimates. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

	Timely			Forecast error		
	(1)	(2)	(3)	(4)	(5)	(6)
Team × WFH	0.041***	0.038***	0.037**	0.024	0.024	-0.010
	(2.611)	(2.747)	(2.215)	(1.245)	(1.250)	(-0.453)
WFH	-0.086	-0.074**	-0.071*	0.483**	0.486**	0.334
	(-1.496)	(-2.433)	(-1.862)	(2.334)	(2.337)	(1.558)
Num firm covered	0.004*	0.002	-0.001	-0.000	-0.000	-0.006
	(1.850)	(1.018)	(-0.384)	(-0.097)	(-0.199)	(-1.199)
Num ind covered	-0.001	0.003	-0.018	-0.026***	-0.026**	-0.028
	(-0.136)	(0.431)	(-1.185)	(-2.603)	(-2.555)	(-1.202)
General exp	-0.002	-0.001	0.022***	0.002	0.002	-0.008
	(-1.164)	(-0.917)	(4.445)	(1.101)	(1.196)	(-0.705)
Firm exp	0.004***	0.002**	-0.022	-0.003***	-0.003***	0.044
	(3.542)	(2.141)	(-0.609)	(-2.619)	(-2.728)	(1.042)
Broker size	0.001	0.001	0.002	0.002	0.001	0.002
	(0.833)	(0.924)	(0.921)	(0.742)	(0.687)	(0.682)
Analyst FE	Y	Y		Y	Y	
Year-month FE		Y	Y		Y	Y
Analyst × Firm FE			Y			Y
Firm × Quarter FE	Y	Y	Y	Y	Y	Y
N	11,750	11,748	7,150	11,514	11,514	7,002
Adj. R^2	0.41	0.51	0.41	0.90	0.90	0.87

Table 5: Dynamics Effect

This table reports the dynamic effects on how working from home affects team and individual analysts differently on two performance measures: the forecast timeliness likelihood and forecast accuracy. The estimated coefficients of following regression model are reported.

$$\begin{aligned} Performance_{ijqt} &= \alpha + \beta_1 Team_i \times 2019Q3_{ijqt} + \beta_2 Team_i \times 2019Q4_{ijqt} + \beta_3 Team_i \times 2020Q1_{ijqt} \\ &+ \beta_3 Team_i \times 2020Q2_{ijqt} + \beta_4 Team_i \times 2020Q3_{ijqt} \\ &+ \mathbf{X}'_{ijqt}\delta + \mu_{jq} + \vartheta_{ij} + \theta_t + \varepsilon_{ijqt} \end{aligned}$$

For brevity, I only keep the interaction terms coefficients. The sample period is from the third quarter of 2019 to the third quarter of 2020. I drop those forecasts which issued in the first quarter but after stay-at-home order and in the second quarter but before the stay-at-home order. The dependent variables are *Timely* and *Forecast error*. *Team* is an indicator which is one if a forecast's associated research report is written by more than one authors and zero otherwise. *2019Q3* is an indicator which is one if a forecast is issued in the third quarter of 2019 and zero otherwise. Other time dummy variables are defined similarly. All variables are defined in the Appendix A1. All continuous variables are winsorized at 1% level. Standard errors clustered at the firm level and the analyst level. *t*-statistics are reported within parentheses under the estimates. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

	Timely			Forecast error		
	(1)	(2)	(3)	(4)	(5)	(6)
Team × 2019Q3	-0.010	-0.006	-0.009	0.005	0.004	-0.014
	(-0.632)	(-0.421)	(-0.589)	(0.389)	(0.345)	(-0.865)
Team × 2019Q4	-0.003	-0.000	-0.002	-0.013	-0.014	-0.017
	(-0.172)	(-0.035)	(-0.160)	(-0.908)	(-0.963)	(-0.972)
Team × 2020Q1	-0.020	-0.016	-0.005	0.034**	0.035**	0.019**
	(-1.316)	(-1.254)	(-0.322)	(2.160)	(2.225)	(2.201)
Team × 2020Q2	0.034**	0.028**	0.037**	0.010	0.009	-0.006
	(2.087)	(1.988)	(2.414)	(0.480)	(0.409)	(-0.273)
Team × 2020Q3	0.006	0.013	0.023	-0.037*	-0.037*	-0.056**
	(0.392)	(0.930)	(1.376)	(-1.859)	(-1.902)	(-2.433)
Control	Y	Y	Y	Y	Y	Y
Analyst FE	Y	Y		Y	Y	
Year-month FE		Y	Y		Y	Y
Analyst × Firm FE			Y			Y
Firm × Quarter FE	Y	Y	Y	Y	Y	Y
N	31,007	31,005	22,707	30,364	30,362	22,246
Adj. R^2	0.43	0.52	0.55	0.90	0.90	0.90

Table 6: Team Size Effect

This table reports the results on the effect of team size on analysts forecast performance measured by forecast timeliness *Timely* and forecast error *Forecast error*. *Team size* is the number of members of a team and it is one for individual analysts. *WFH* is an indicator which is one if a forecast is made by the analyst after the stay-at-home policy in the state where the analyst is located, and zero otherwise. All variables are defined in the Appendix A1. All continuous variables are winsorized at 1% level. Standard errors clustered at the firm level and the analyst level. *t*-statistics are reported within parentheses under the estimates. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

	Timely						Forecast error					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Team size × WFH	0.020***	0.019***	0.016**	0.018	0.018	0.052	0.013	0.013	0.004	-0.005	-0.008	-0.055
	(3.027)	(3.125)	(2.081)	(0.558)	(0.642)	(1.580)	(1.566)	(1.520)	(0.410)	(-0.139)	(-0.216)	(-1.152)
Team size^2 × WFH				0.000	0.000	-0.007				0.002**	0.001**	0.012**
				(0.071)	(0.043)	(-1.167)				(2.222)	(2.129)	(2.278)
WFH	-0.105*	-0.091***	-0.083**	-0.103	-0.090**	-0.114**	-0.496**	-0.499**	-0.343	-0.489**	-0.495**	-0.289
	(-1.769)	(-2.843)	(-2.045)	(-1.612)	(-2.359)	(-2.374)	(-2.376)	(-2.376)	(-1.618)	(-2.377)	(-2.392)	(-1.315)
Num firm covered	0.003*	0.002	-0.001	0.003*	0.002	-0.001	-0.000	-0.000	-0.006	-0.000	-0.000	-0.006
	(1.826)	(0.990)	(-0.428)	(1.826)	(0.990)	(-0.401)	(-0.116)	(-0.216)	(-1.196)	(-0.117)	(-0.217)	(-1.230)
Num ind covered	-0.001	0.004	-0.017	-0.001	0.004	-0.018	-0.025**	-0.025**	-0.026	-0.025**	-0.025**	-0.025
	(-0.063)	(0.510)	(-1.119)	(-0.061)	(0.509)	(-1.151)	(-2.556)	(-2.511)	(-1.151)	(-2.548)	(-2.506)	(-1.088)
General exp	-0.002	-0.001	0.022***	-0.002	-0.001	0.022***	0.002	0.002	-0.008	0.002	0.002	-0.007
	(-1.182)	(-0.937)	(4.416)	(-1.183)	(-0.938)	(4.437)	(1.088)	(1.184)	(-0.698)	(1.082)	(1.180)	(-0.664)
Firm exp	0.004***	0.002**	-0.023	0.004***	0.002**	-0.023	-0.003***	-0.003***	0.044	-0.003***	-0.003***	0.043
	(3.532)	(2.128)	(-0.658)	(3.532)	(2.128)	(-0.635)	(-2.629)	(-2.737)	(1.050)	(-2.629)	(-2.737)	(1.028)
Broker size	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.002	0.001	0.001	0.002
	(0.795)	(0.882)	(0.881)	(0.784)	(0.872)	(0.934)	(0.728)	(0.671)	(0.748)	(0.724)	(0.671)	(0.696)
Analyst FE	Y	Y		Y	Y		Y	Y		Y	Y	
Year-month FE		Y	Y		Y	Y		Y	Y		Y	Y
Analyst × Firm FE			Y			Y			Y			Y
Firm × Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	11,750	11,748	7,150	11,750	11,748	7,150	11,514	11,514	7,002	11,514	11,514	7,002
Adj. R^2	0.41	0.51	0.41	0.41	0.51	0.41	0.90	0.90	0.87	0.90	0.90	0.87

Table 7: Robustness Tests

This table reports the robustness tests results. For brevity, I only report the estimated results on *WFH* × *Team*. I repeat the analyses in Table 4 with different control groups. Now *WFH* is an indicator which is one if a forecast is issued in year 2020 and zero otherwise. All variables are defined in the Appendix A1. All continuous variables are winsorized at 1% level. Standard errors clustered at the firm level and the analyst level. t-statistics are reported within parentheses under the estimates. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

	Timely			Forecast error		
	(1)	(2)	(3)	(4)	(5)	(6)
Team × WFH	0.047***	0.043***	0.079***	-0.016	-0.018	-0.040
	(2.613)	(2.634)	(3.858)	(-0.751)	(-0.836)	(-1.266)
Control	Y	Y	Y	Y	Y	Y
Analyst FE	Y	Y		Y	Y	
Year-month FE		Y	Y		Y	Y
Analyst × Firm FE			Y			Y
Firm × Quarter FE	Y	Y	Y	Y	Y	Y
N	14,769	14,769	8,113	14,479	14,479	7,992
Adj. R^2	0.41	0.49	0.42	0.89	0.89	0.85

Table 8: WFH and Analysts Forecast Timeliness–Continuous Measure

This table reports the results on the effect of WFH on analysts forecast timeliness measured by a continuous variable *Delay* defined as the gap between the forecast date and the earnings announcement date. *Team* is an indicator which is one if a forecast is made by more than one analyst and zero otherwise. *WFH* is an indicator which is one if a forecast is made by the analyst after the stay-at-home policy in the state where the analyst is located, and zero otherwise. All variables are defined in the Appendix A1. All continuous variables are winsorized at 1% level. Standard errors clustered at the firm level and the analyst level. t-statistics are reported within parentheses under the estimates. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

	Delay			Log(1+Delay)		
	(1)	(2)	(3)	(4)	(5)	(6)
Team × WFH	-0.349	-0.161	-0.253	-0.036	-0.024	-0.012
	(-0.941)	(-0.950)	(-1.262)	(-1.145)	(-1.049)	(-0.492)
WFH	1.614	0.655	1.139	0.248	0.191	0.154
	(0.622)	(0.786)	(0.891)	(1.032)	(1.597)	(1.117)
Num firm covered	-0.143**	-0.025	-0.020	-0.013***	-0.005*	-0.002
	(-2.038)	(-1.133)	(-0.417)	(-2.801)	(-1.944)	(-0.360)
Num ind covered	0.225	-0.073	0.000	0.020	0.001	0.029
	(0.789)	(-0.654)	(0.001)	(1.004)	(0.077)	(1.219)
General exp	0.068	0.017	-0.412***	0.006	0.003	-0.049***
	(1.255)	(0.651)	(-2.775)	(1.402)	(1.033)	(-4.467)
Firm exp	-0.107***	-0.021**	1.616	-0.010***	-0.003**	0.144
	(-3.612)	(-2.275)	(1.149)	(-4.486)	(-2.536)	(1.327)
Broker size	0.011	0.013	-0.001	-0.004	-0.003	-0.004
	(0.194)	(0.762)	(-0.064)	(-0.967)	(-1.278)	(-1.629)
Analyst FE	Y	Y		Y	Y	
Year-month FE		Y	Y		Y	Y
Analyst × Firm FE			Y			Y
Firm × Quarter FE	Y	Y	Y	Y	Y	Y
N	11,683	11,681	7,083	11,683	11,681	7,083
Adj. R^2	0.28	0.90	0.81	0.41	0.77	0.65

Table 9: Market Reaction

This table reports the results on the market raction to team and individual analysts. The dependent variables are $CAR[0, +1]$ calculated as two-day cumulative abnormal returns from the day when an analyst issues a forecast to the following day after that released day. The abnormal returns are estimated based on a market model. All variables are defined in the Appendix A1. All continuous variables are winsorized at 1% level. Standard errors clustered at the firm level and the analyst level. t-statistics are reported within parentheses under the estimates. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

	CAR[0,+1]		
	(1)	(2)	(3)
Team × WFH	0.099***	0.100**	0.292**
	(3.532)	(2.236)	(2.367)
WFH	1.544	1.543	0.661
	(0.556)	(0.556)	(0.190)
Num firm covered	-0.008	-0.004	0.035
	(-0.358)	(-0.179)	(0.565)
Num ind covered	0.147	0.158	0.112
	(1.255)	(1.367)	(0.461)
General exp	-0.043**	-0.046**	-0.462***
	(-2.171)	(-2.373)	(-4.600)
Firm exp	-0.010	-0.010	2.659***
	(-0.808)	(-0.797)	(4.958)
Broker size	-0.001	-0.007	-0.024
	(-0.065)	(-0.309)	(-0.846)
Delay	-0.008	0.038	0.032
	(-0.834)	(1.318)	(0.751)
Analyst FE	Y	Y	
Year-month FE		Y	Y
Analyst × Firm FE			Y
Firm × Quarter FE	Y	Y	Y
N	11,213	11,211	6,621
Adj. R^2	0.71	0.71	0.65

Table 10: Other Analysts Activities

This table reports the results on how working from home affects team and individual analysts differently on other analyst activities. The dependent variables are *Forecast update* and *Log(1+Page num)*. *Team* is an indicator which is one if a forecast's associated research report is written by more than one authors and zero otherwise. *WFH* is an indicator which is one if a forecast is made by the analyst after the stay-at-home policy in the state where the analyst is located and zero otherwise. All continuous variables are winsorized at 1% level. Standard errors clustered at the firm level and the analyst level. *t*-statistics are reported within parentheses under the estimates. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

	Forecast update			Log(1+Num page)		
	(1)	(2)	(3)	(4)	(5)	(6)
Team × WFH	-0.114**	-0.115**	-0.143***	0.038**	0.040***	0.040**
	(0.048)	(0.047)	(0.054)	(0.015)	(0.015)	(0.018)
WFH	0.066	0.073	0.016	0.008	-0.008	-0.025
	(0.197)	(0.198)	(0.318)	(0.113)	(0.119)	(0.129)
Num firm covered	0.006*	0.006	0.027***	0.004	0.004*	-0.002
	(0.004)	(0.004)	(0.011)	(0.003)	(0.003)	(0.004)
Num ind covered	-0.007	-0.005	-0.045	-0.012	-0.012	-0.001
	(0.017)	(0.018)	(0.036)	(0.011)	(0.010)	(0.015)
General exp	-0.005	-0.005	-0.031	-0.003	-0.004*	-0.005
	(0.004)	(0.004)	(0.019)	(0.002)	(0.002)	(0.005)
Firm exp	0.003*	0.003	-0.116	-0.002	-0.001	-0.021
	(0.002)	(0.002)	(0.085)	(0.001)	(0.001)	(0.042)
Broker size	-0.001	-0.001	-0.004	-0.001	-0.001	-0.002
	(0.004)	(0.004)	(0.005)	(0.002)	(0.002)	(0.002)
Analyst FE	Y	Y		Y	Y	
Year-month FE		Y	Y		Y	Y
Analyst × Firm FE			Y			Y
Firm × Quarter FE	Y	Y	Y	Y	Y	Y
N	11,750	11,748	7,150	11,573	11,571	7,008
Adj. R^2	0.53	0.54	0.32	0.56	0.59	0.50

Appendix

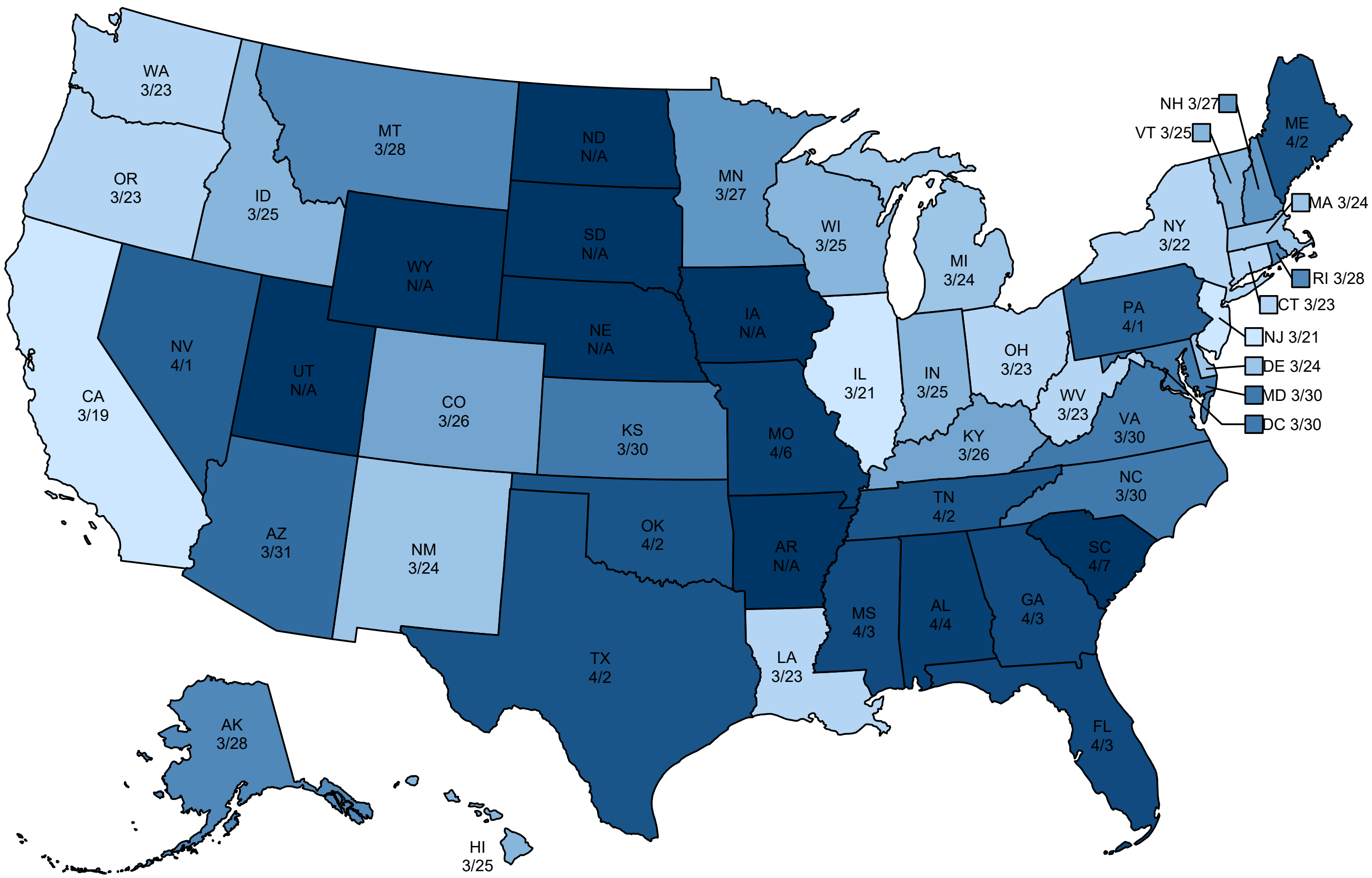

Figure A1: Announcement Date of Stay-at-home Orders across U.S. States

This figure plots announcement dates of stay-at-home orders of U.S. states. The date with the format "month/day" is shown below state codes. If a state does not announce a stay-at-home order, the date is "N/A". The darker the color, the later the state announces the order.

Table A1: Variable Definitions and Sources

This table reports the definition of variables and their data sources.

Variable	Definition	Source
Broker size$_{it}$	The number of analysts employed by the brokerage house where analyst i is working at time t.	I/B/E/S
CAR$[0,+1]_{ijt}$	The two-day cumulative abnormal returns from the day when analyst i issues a forecast for firm j at time t to the following day after that released day. The abnormal returns are estimated based on a market model.	CRSP
Delay$_{ijt}$	The gap between date t when analyst i issues a forecast for firm j and the firm j's latest earnings announcement date.	I/B/E/S
Firm exp$_{ijt}$	The number of years analyst i covers the firm j. It is the difference between the forecast date t and the date of the analyst's first earnings estimate for the firm on I/B/E/S, scaled by 365.	I/B/E/S
Forecast error$_{ijqt}$	$100 \times \frac{\lvert \text{Actual EPS}_{jt} - \text{Forecasted EPS}_{ijt} \rvert}{\text{Stock price}_{jq-4}}$	I/B/E/S
Forecast update$_{ijqt}$	The number of forecasts revisions for the first forecast issued by analyst i for firm i in quarter q at time t.	I/B/E/S
General exp$_{it}$	The number of years analyst i has been in I/B/E/S. It is the difference between the forecast date t and the date of the analyst's first earnings estimate on I/B/E/S, scaled by 365.	I/B/E/S
Num firm covered$_{it}$	The number of firms analyst i covers at time t.	I/B/E/S
Num ind covered$_{jt}$	The number of two-digit SIC industries analyst i covers at time t.	I/B/E/S
Num pages$_{ijqt}$	The number of pages of analyst reports written by analyst i for firm j of quarter q at time t.	Eikon
Team size$_{i}$	The number of analysts in the analyst team i. If analyst i is an individual analyst, the value is one.	I/B/E/S; Eikon
Team$_{i}$	Dummy variable which is one if analyst i in I/B/E/S is consist of more than one analyst and zero otherwise.	I/B/E/S; Eikon
Timely$_{ijqt}$	Dummy variable which is one if analyst i's earnings forecast for firm j in time t is issued within one trading day after firm j's quarter q earnings announcement date.	I/B/E/S
WFH$_{ijqt}$	Dummy variable which is one if the time t when analyst i issues earnings forecast for firm j in quarter q is later than the stay-at-home policy in the state where analyst i is located, and zero otherwise	Online Sources