Locked-in at Home: Female Analysts' Attention at Work during the COVID-19 Pandemic

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Abstract

This paper explores the shock of school closures caused by the COVID-19 pandemic to study the effect of domestic responsibilities on analysts' attention at work. School closures significantly reduce the forecast timeliness of female analysts rather than that of male analysts. Using manually-collected data on whether analysts have children, I show that mothers are 20% less likely to issue timely forecasts after school closures. Professional women are more likely to get distracted from work by domestic duties, which makes it harder for them to be as successful as their male counterparts in competitive industries.

JEL-Classification Codes: G24, G41, J16, J22

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1 Introduction

Despite the rise in women's labor market participation over the past decades, women are still underrepresented and earn less than men in many competitive industries. For example, among financial analysts in the U.S., only around 10% are female in 2020, and the gender pay gap amounts to $19,604 per annum in 2019.[1] Female analysts are successful women who self-select into this competitive and lucrative industry (Kumar (2010)) and have similar backgrounds to male analysts (Fang and Huang (2017)). It is unlikely that there are significant gender differences among financial analysts in preferences for competition or risk aversion comparable to those found in the general population (Niederle and Vesterlund (2007) and Dwyer et al. (2002)). What could be the reason that prevents professional women from being equally successful in competitive industries?

Among studies explaining the gender gap, Becker (1985) models the allocation of human capital between domestic and market work. The model indicates that women spend more time and effort in domestic work and have less time and effort per unit of time for market work, leading to gender pay gap and occupational gender segregation. Is the female analysts' attention at work more likely to be influenced by domestic burdens?[2] If so, the gender inequality in the allocation of domestic work at least partially explains the gender gap in this competitive industry.

In this paper, I take advantage of a quasi-natural experiment in which schools are exogenously closed by states during the COVID-19 pandemic to study whether female analysts are more likely

[1] The fraction of female analysts is based on the 2020 sample in this paper. The percentage of female analysts fluctuates between 10% and 14% from 1993 to 2009, with an average of 12% in the sample of Fang and Huang (2017). The gender pay gap among financial analysts is obtained from U.S. Bureau of Labor Statistics. See `https://www.bls.gov/cps/cpsaat39.htm`.

[2] I do not distinguish the definition of attention and effort in this paper, as common in the psychology literature (e.g., Kahneman (1973)). Attention and effort both refer to limited human resources at a given time in this paper.

to be influenced by an increase in domestic responsibilities. The school closures caused by the COVID-19 pandemic in 2020 affected more than 55.1 million students in 124,000 schools in the U.S.[3] The large-scale and unexpected school closures led to a significant increase in the childcare demand at home (e.g., Power (2020)). Each state decided on school closures independently after the pandemic started. Hence, the school closures can be viewed as exogenous to people's labor market activities and provide a unique opportunity to study how domestic duties influence attention at work of professional men and women differently.

The profession of sell-side equity analysts is a good setting to study the effect of domestic burdens on attention at work. First, sell-side analysts usually work for a long time and are required to have high attention to process new information and give timely responses (Bradshaw (2011), Bradshaw et al. (2017), and Brown et al. (2015)). Therefore, it is possible to capture and quantify the influence of limited attention on analysts' forecast timeliness when they are overburdened by household responsibilities. Second, the profession is highly competitive. People who self-select into this industry are likely to be homogeneous in many aspects, such as education, risk aversion, and preference for competitiveness. Hence, it is implausible that observed differences in forecasting activities are from gender differences in preference or abilities. Male analysts constitute a valid control group in the investigation of the effect of an increase in domestic responsibilities on female analysts' forecast activities. Last, corporate earnings announcements and analysts' forecast releases have detailed timestamps in the data, making it possible to observe the change in forecasting behavior in the short window around the COVID-19 school closures.

[3] Statistics from Map: Coronavirus and School Closures (2020, March 6), Education Week, Retrieved May 2020, see `https://www.edweek.org/ew/section/multimedia/map-coronavirus-and-school-closures.html`.

Limited attention of analysts is most likely to have a negative impact on forecast timeliness. By contrast, whether limited attention influences forecast boldness and accuracy may not be as clear because issuing bold and accurate forecasts may represent abilities of analysts that are less likely to be influenced by distractions. Driskill et al. (2020) find that limited attention caused by multiple simultaneous earnings announcements negatively influences analysts' forecast timeliness. They do not conduct analyses on forecast accuracy because analysts can improve accuracy by delaying forecasts (Cooper et al. (2001) and Clement and Tse (2003)).[4] In a similar vein, I also mainly focus on forecast timeliness in this paper. It is important to understand how distractions of domestic work influence the forecast timeliness of financial analysts because analysts' timely reactions to new information have important implications for financial markets and analysts' career outcomes (Zhang (2008) and Chiu et al. (2021)).[5]

I conduct a difference-in-differences estimation by running a regression of the analyst forecast timeliness on a female dummy, a school closure dummy, and their interactions for a sample of earnings forecasts around the school closures caused by the COVID-19 pandemic, controlling for various firm and analyst characteristics, firm, broker and state (or analyst), and time fixed effects. Including analyst fixed effects helps rule out time-invariant analysts' characteristics such as their general capability and habits on forecast releases.

After the school closures, the probability of female analysts' issuing timely forecasts within one day after earnings announcements decreases at a much larger magnitude than that of male analysts'

[4]Driskill et al. (2020) also mention that they do not examine forecast boldness and accuracy improvement because they would like to avoid using benchmarks before earnings announcements when defining relative measures of forecast boldness and accuracy improvement.

[5]Chen et al. (2010), Livnat and Zhang (2012), and Huang et al. (2018) study analysts' roles of information interpretation or information discovery by investigating timely forecasts.

in the first two quarters of 2020: the coefficient estimate of the interaction term between the female dummy and the school closure dummy is 6.7 percentage points (pp) and is statistically significant at the 1% level. The effect exists even after controlling for firm $\times$ quarter fixed effects, which effectively compares within analyst forecasts after the same firm's same earnings announcement. School closures do not have a significantly negative effect on male analysts' forecast timeliness when analyst fixed effects are controlled for.

Exploring the staggered beginning of school closures across states by using a sample of earnings forecasts in a shorter time window of March 2020, I find that female analysts are 12.2 pp less likely to issue timely forecasts after school closures, which accounts for 16.5% of the average probability to issue a timely forecast in the sample. Moreover, to rule out the influence of seasonality (e.g., Lo and Wu (2018)), I compare the timeliness of earnings forecasts issued after all states decided to close schools, i.e., from March 23rd, 2020 to the end of the sample in August 2020, with the timeliness of earnings forecasts issued in the same time period in 2019. I find similar results: female analysts' forecast timeliness decreases by 4.8 pp after school closures in 2020.

If the unequal division of labor between sexes in domestic work leads to the observed different effects of school closures on forecast timeliness between male and female analysts, I expect the phenomenon to be more salient in states with conservative gender attitudes because the gender imbalance in the allocation of housework is more salient in these states (Ruppanner and Maume (2016)), and financial analysts may conform to expectations of their social environment. I use the U.S. 2017 wave of the World Value Survey to calculate a measure of gender attitudes and divide states into liberal- or conservative- gender-attitude states with this measure. The results show that the negative effect of COVID-19 school closures on female analysts' forecast timeliness in states with conservative gender attitudes is about twice as large as that in states with liberal gender attitudes.

Since the time of COVID-19 school closures overlaps with a financial crash, I conduct a placebo test on whether there is any gender difference in analysts' forecast timeliness during financial crises. I find no robust gender difference in forecast timeliness during the 2001 or 2008 financial crises. Furthermore, I explore another school closure event during the 2009 H1N1 pandemic and find a significant reduction in female analysts' forecast timeliness after that school closure as well.

Analyses comparing the effects of school closures on forecast timeliness between male and female analysts estimate the average effect among all analysts with or without children. To better attribute the effect of school closures on forecast timeliness to an increase in the childcare responsibilities, I manually collect information on whether analysts have children by checking their Facebook pages. With this novel data, I show that compared within female analysts, analysts with children are 13.1 pp less likely to issue timely forecasts, and compared within analysts that have non-adult children, female analysts are 22.6 pp less likely to issue timely forecasts. The triple difference estimation identifies that the increase in domestic responsibilities after school closures reduces the forecast timeliness of mothers by 15% to 20%. These findings rule out potential explanations of gender differences in risk aversion or overconfidence, because female analysts without non-adult children are not more influenced by the COVID-19 school closures, compared with male analysts.

In addition to how long it takes analysts to issue the first forecasts after firms' earnings announcements, the pressure of domestic burdens after the COVID-19 school closures may also change the time of day when female analysts work. The literature has examined the seasonality of analysts' forecasts (Lo and Wu (2018) and Chang et al. (2017)), but little is known about factors that influence the exact time of day analysts issue earnings forecasts. If female analysts are distracted by domestic responsibilities, they may shift their forecast release time to the time periods without intensive housework or childcare activities. I find that female analysts are more than 9 pp less likely to release forecasts during housework-intensive hours after the COVID-19 school closures while male analysts barely change their forecast release time.

Regarding other important measures of forecast quality, it is unclear whether the COVID-19 school closures influence forecast boldness and forecast accuracy, as mentioned earlier. There is some evidence that female analysts' forecasts deviate more from the consensus of available analysts' forecasts after school closures, probably because they do not pay as much attention to the available forecasts as they did before the school closures. The effect of the school closures on the deviation from the analysts' own previous forecast is statistically insignificant and economically small. There is no strong evidence that the school closures deteriorate forecast accuracy, either.

At last, I study the effect of the school closures on analysts' activities at earnings conference calls. I find some evidence that after school closures, female analysts are less likely to ask questions at conference calls that are held early in the morning or at noon. In addition, female analysts tend to ask shorter and fewer questions at earnings conference calls after the school closures.

This paper is the first to investigate the causal effect of the distraction of domestic duties on the supply of analyst services. Previous literature shows that analysts are less productive in processing information when encountering unpleasant weather (Dehaan et al. (2017)), decision fatigue over the course of a day (Hirshleifer et al. (2019)), or simultaneous earnings announcements of firms they cover (Driskill et al. (2020)). In addition, analysts promptly respond to the needs of institutional investors (Chiu et al. (2021)) and issue recommendations when the investor demand or the information supply of earnings announcements is high (Yezegel (2015)). This paper enhances understanding of analysts' forecast activities by examining a new factor that affects analysts' attention at work: domestic responsibilities. In this sense, the paper also adds to the broader literature on sources of distractions that lead to limited attention in the financial market.[6]

The paper closely relates to the literature on the gender difference in the financial analyst industry (Kumar (2010) and Fang and Huang (2017)). Many papers in economics have examined the causes of the gender gap in the labor market.[7] This paper provides empirical evidence for the sexual division of labor theory in Becker (1985) in the setting of sell-side equity analysts: female analysts, especially mothers, suffer more from limited attention and have to reduce forecast timeliness when facing an increase in domestic burdens. Given that analysts constantly producing timely forecasts gain better career outcomes (Chiu et al. (2021)), the unequal allocation of household responsibilities puts female analysts in an unfavorable position in the financial analyst labor market.

Finally, the paper contributes to the growing literature on the effect of COVID-19 on financial markets (e.g., Ding et al. (2020) and Landier and Thesmar (2020)) and social inequality (e.g., Alon et al. (2020), Brown and Ravallion (2020), Barber et al. (2020), and Collins et al. (2021)). This paper quantifies the negative effects of the COVID-19 school closures on professional mothers. Even though female analysts are skilled and competitive, they are still more likely to be influenced

[6]For example, Hirshleifer et al. (2009) find that investors suffer from limited attention in the face of extraneous events. DellaVigna and Pollet (2009) and Louis and Sun (2010) find that investors are distracted on Fridays.

[7]Previous studies attribute the gender gap in the labor market to e.g., different preferences (Niederle and Vesterlund (2007)) or discrimination (e.g., Neumark et al. (1996) and Goldin and Rouse (2000).

by domestic burdens after school closures than male analysts. It should be noted that lock-down measures unequally influence different groups.

2 Data and summary statistics

2.1 Sample construction

The earnings announcements and individual analysts' earnings forecasts are from the I/B/E/S database. The time stamps of earnings announcements and analyst forecasts must be available in order to measure timeliness of forecasts. Therefore, the sample period starts from January 1999 when timestamps become widely covered in the I/B/E/S database, and ends in August 2020. Following Driskill et al. (2020) and Zhang (2008), I use the sample of the first forecast by each analyst for a firm's earnings in quarter t+1 issued after the firm's quarter t earnings announcement but before one day prior to its quarter t+1 earnings announcement. To be included in the sample, the earnings announcement dates for both quarter t and t+1 must be available. I merge the I/B/E/S data with CRSP and Compustat databases to obtain stock price and accounting information of the firm as of quarter t.

Following previous literature (e.g., DeHaan et al. (2015)), I exclude earnings announcements if the announcement date is more than 90 days after the fiscal quarter-end. I drop penny stocks with the stock price below $1 as of the fiscal end of quarter t. In addition, the first and the last coverage of an analyst following a firm and firms with fewer than two following analysts in the quarter are excluded from the sample. After these screening procedures, the sample includes 1,205,409 firm-quarter-analyst observations.

The main sample finally includes earnings announcements of the first two quarters in 2020 because primary analyses are around the COVID-19 school closures which started in March 2020. In this way, I construct a roughly symmetric window around the school closure events. This is sensible because a larger time window may include confounding events that influence the demand for domestic work and the gender difference in forecast timeliness.

A potential problem of the sample could be that for a given earnings announcement, analyst forecasts before school closures tend to be systematically more timely than analysts forecasts after school closures. To avoid capturing this systematic effect of school closures on forecast timeliness, I exclude earnings announcements from the sample if earnings announcements happened before school closures in a state, and a forecast of an analyst in that state was issued after school closures.

Figure 1 gives examples to demonstrate the exclusion of these observations. In Scenario 1, Firm A had an earnings announcement before Analyst 1's school closure date, and Analyst 1's forecast for Firm A was released after the school closure. This earnings announcement was also before Analyst 2's earnings forecast, but Analyst 2 issued a forecast before the school closure. If the analyst forecasts for Firm A were not excluded from the sample, Analyst 1's forecast would be regarded as an after-school-closure forecast while Analyst 2's forecast would be regarded as a before-school-closure forecast. In this case, before-school-closure forecasts are systematically more timely than after-school-closure forecasts. By contrast, the case demonstrated in Scenario 2 does not need to be excluded from the sample: both Firm B's earnings announcements and Analyst 3's forecast happened after Analyst 3's school closures, and both Firm B's earnings announcements and Analyst 4's forecast happened before Analyst 4's school closures. In this case, there is no systematic effect of school closures on forecast timeliness, and the staggered beginning of school closing across states creates the variation in the definition of the school closure indicator for each analyst forecast. I exclude the 11,247 observations involving earnings announcements before the school closures of a state and an analyst in that state issued forecasts after the school closures.[8]

The main sample includes 18,750 firm-quarter-analyst observations, with 2,201 firms and 1,880 analysts, out of which 201 are female analysts. Thereafter, summary statistics and discussions refer to the sample from January 2020 to August 2020 after the screening procedures as described above in this section, unless otherwise pointed out.

To measure forecast timeliness, I calculate the number of trading days between the earnings announcement date of firm i for quarter t and the date when analyst j releases earnings forecast for quarter t+1 of firm i in this sample. Following previous literature on analyst forecast timeliness (Zhang (2008), Driskill et al. (2020) and Chiu et al. (2021)), I define a dummy variable $Timely_{i,j,t}$, which is equal to one if analyst j issues the earnings forecast for quarter t+1 within one trading day (day 0 or day1) after the firm i's quarter t earnings announcement date, and zero otherwise.[9]

[8]Note that the exclusion of these observations aims to sensibly estimate the school closure effects. The main focus is the gender difference of the school closure effects, which should not be biased by including these observations. Table IA1 in the Internet Appendix shows that including observations with earnings announcements demonstrated in Figure 1 Scenario 1 does not influence the main results. However, the effect of school closures on forecast timeliness is significantly biased upward: the coefficient estimate of *School closure* is exaggerated to -20 pp, and the bias is even larger after controlling for time fixed effects.

[9]The forecast timeliness is measured by a dummy variable to minimize the influence of extreme values because the distribution of the number of days between earnings announcements and analyst forecasts is highly skewed (Zhang (2008)). In my sample, the number of days between earnings announcements and analyst forecasts has a mean of 3.75, a median of 1 and a standard deviation of 10. Even the log form of the measure is highly positive-skewed. Table IA2 in the Internet Appendix shows baseline results using the log form of this continuous measure as a dependent variable. The gender difference in the effect of school closures on forecast timeliness is still economically large, i.e., 6.7% to 8.9%.

2.2 School closure

Data on the school closure time are manually collected online. The start of school closures is based on the timestamps of the media coverage on school closure decisions of the state or official documents issued by the governors because first, people started to arrange their work and life to adapt to the coming school closure at the time of announcement of school closures; second, many schools started to shorten the teaching time or close after the state announced the school closure decision and before the required latest closure dates. The map in Appendix A contains manually-collected school closure dates, which range from March 7th to March 23rd. The darker the color of the state is, the earlier school closures started. California and Kentucky are among the first states announcing school closure decisions.

$School\ closure_{i,j,t}$ is defined as a dummy variable equal to one, if schools are closed in the state where analyst j is located at the time of firm i's earnings announcement for quarter t, and zero otherwise.

2.3 Analysts' gender, location and family conditions

I/B/E/S only provides analysts' last names and the initial of their first names. In order to identify the gender of the analysts, I manually collect the full name and identify their gender based on their Linkedin profiles, official websites of the brokers or media coverage. If I cannot identify the gender from the information online including their photos and the third-person pronoun "he" or "she" in the media coverage, I infer the gender from the analyst's first name. Analyst location data are obtained from the BrokerCheck website by FINRA.[10] I can determine the gender of analysts for 97.7% of the sample and the location for 91.7% of the sample.

Furthermore, I collect data on whether analysts have non-adult children by checking each analyst's Facebook page. Internet Appendix I describes the procedure of finding analysts' Facebook pages, checking whether they have children, and estimating the ages of their children. I find Facebook pages for 680 analysts. 262 of these analysts have children under 18 based on their Facebook. All variables are defined in Appendix B.

2.4 Summary statistics

Table 1 reports statistics on variables used in the main analyses. In the sample, 10% of the analysts are female and 64% of the earnings forecasts were released after the COVID-19 school closures. On average, an analyst follows around 18 firms in the quarter, works in a brokerage with 45 analysts, and has 23 quarters of firm-specific experience. *No. of followed firm's EA* is a factor that influences the level of an analyst's distraction (Driskill et al. (2020)): on average, an analyst has 0.82 additional firms that announces earnings forecasts on the earnings announcement date of firm i. [11]

Table 2 shows the difference between female analysts and male analysts in the main sample of 2020. *t*-statistics are based on univariate regressions of the variables on the female dummy and standard errors are clustered by analyst and firm. For most variables, the difference between male and female analysts is economically small and statistically insignificant. The modest difference between gender is expected, given that only competitive women self-select into and survive in the

[10] `https://brokercheck.finra.org/`. The website provides a time series of firms and locations where an analyst registers.

[11] Table IA3 in Internet Appendix presents correlations between the variables used in the analysis. They show that multicollinearity should not be an issue in the regressions.

financial analyst industry. Female analysts tend to issue slightly more timely forecasts than male analysts. On the contrary, male analysts issue more accurate forecasts than female analysts in the sample.[12] In addition, female analysts work in larger brokerage firms than male analysts, which is consistent with summary statistics in Fang and Huang (2017). I carefully control for these variables that are expected to affect forecast timeliness in the analyses.

Figure 2 plots the probability of issuing timely forecasts among male and female analysts over a 9-week event window surrounding the exogenous shock in childcare demands. It shows that the forecast timeliness is trending closely in parallel for male and female analysts in the 4 weeks before the school closures. Female analysts issue more timely forecasts than male analysts before school closures. School closures decrease forecast timeliness of both male and female analysts right in the week of school closure announcements, but the negative effect is visually larger for female analysts.

Extending the sample to previous years, Internet Appendix Table IA1 plots the evolution of forecast timeliness from 1999 to 2020. Male analysts are more likely to issue timely forecasts than female analysts before 2009, but female analysts' forecasts become more timely than male analysts' forecasts since 2010. The significant change in the gender difference in forecast timeliness over time justifies the choice of a short time window when I analyze the effect of COVID-19 school closures.

[12]There are mixed findings on the gender difference in forecast accuracy in the previous literature: Kumar (2010) shows that female analysts issue more accurate forecasts than male analysts while Fang and Huang (2017) find that connected male analysts issue more accurate forecasts than female analysts.

3 Domestic work distractions and analyst forecast timeliness

3.1 Forecast timeliness after the COVID-19 school closures

Forecast timeliness is an important perspective to assess the quality of analyst earnings forecasts. Investors care about timeliness of analysts' forecasts, and timely earnings forecasts have a more significant price impact than delayed ones (Cooper et al. (2001)). Timely forecasts also play an important role in improving market efficiency, in the sense that they facilitate price discovery (Zhang (2008)). Forecast timeliness influences analysts career outcomes as well: Chiu et al. (2021) find that analysts producing timely forecasts are more likely to be voted as an all-star analyst and less likely to be demoted to a smaller brokerage firm.

When financial analysts have limited attention, it is more difficult for them to issue timely forecasts because they cannot respond fast to new information. Driskill et al. (2020) show that analysts with limited attention issue less timely forecasts by studying the effect of concurrent firms' earnings announcements in the analysts' coverage portfolio on forecast timeliness. In this study, the increase in the childcare demand during school closures is an exogenous distraction for analysts and may reduce the timeliness of their forecasts.

Women spend more time on parenting and other domestic tasks than men (e.g., Bertrand et al. (2010)). According to Becker (1985), the optimal amount of effort allocated to an hour of an activity is proportional to the effort intensity of the activity. The allocation of time that does not change effort intensities changes the effort per hour in all activities. When women spend more time on energy-consuming domestic activities such as childcare, they have not only less time left for market work but also less energy for each hour of market work. Therefore, I expect the exogenous increase in domestic work after COVID-19 school closures are more likely to distract female analysts rather than male analysts, and decrease their forecast timeliness.

I test the effect of domestic responsibilities on the timeliness of analyst forecasts by exploring the exogenous school closure decisions during the COVID-19 pandemic in the following difference-in-differences model:

$$\begin{aligned} Timely_{i,j,t} =& \alpha + \beta_1 Female_j \times School\,closure_{i,j,t} + \beta_2 Female_j + \beta_3 School\,closure_{i,j,t} \\ &+ Controls + u_i + v_j + z_t + \varepsilon_{i,j,t}, \end{aligned} \tag{1}$$

where $Female_j$ is a dummy variable equal to one if the analyst is a female, and zero otherwise; $School\,closure_{i,j,t}$ indicates whether school closures start when analyst j issues earnings forecasts for firm i after the earnings announcement as of quarter t. The regression includes firm fixed effects, analyst fixed effects, and time fixed effects to control for time invariant characteristics of firms and analysts, and the time trend.[13] Including analyst fixed effects takes care of any general capability, work habits, attitudes, education, and personality traits etc. that may impact the likelihood to issue timely or non-timely forecasts. Standard errors clustered by analyst and firm.

Table 3 contains the regression results. In Column (1), the model compares the forecast timeliness of analysts after controlling for firm, broker, state, and time fixed effects. Female analysts' forecast timeliness decreases at a 4.3 pp larger magnitude than that of male analysts, and the gender difference is statistically significant at the 10% level. The COVID-19 school closures decrease forecast timeliness of male analysts by 6.4 percentage points (pp) and the effect is statistically sig-

[13] Time fixed effects control for the earnings announcement date of firm i in quarter t. Therefore, any calendar time effect such as the day of a week is controlled for.

nificant at the 5% level. When schools are not closed in 2020, female analysts are 4.9 pp more likely to issue timely forecasts, compared with male analysts. Adding to the findings in Kumar (2010) that female analysts issue more accurate and bolder forecasts than male analysts, I show that they issue more timely forecasts in 2020 when schools are not closed.

The model in Column (2) additionally controls for analyst fixed effects and compares the forecast timeliness within an analyst. After controlling for time-invariant characteristics of analysts, the coefficient estimate of the interaction term of *Female* and *School closure* goes up to 6.7 pp, which is statistically significant at the 1% level. The difference is economically significant as well, given that it accounts for 9.05% of the average forecast timeliness in the sample (Table 1). On the contrary, the negative effect of the COVID-19 school closures on forecast timeliness among male analysts decreases to half of the effect in the model without analyst fixed effects in Column (1) and becomes statistically insignificant.

The model in Column (3) controls for firm × quarter fixed effects. The model is very strict because it effectively compares within analyst forecasts after the same firm's same earnings announcement. The sample allows this comparison since there are earnings announcements and analysts' forecasts both happening before the school closure in one state and both happening after the school closure in another state (Scenario 2 demonstrated in Figure 1). Again, the negative effect of school closures on forecast timeliness is 6.2 pp larger among female analysts than male analysts within the same firm-quarter, which is statistically significant at the 1% level.

Several control variables significantly influence forecast timeliness. Consistent with the findings in Driskill et al. (2020), the number of followed firms' earnings announcements has a negative effect on forecast timeliness. Specifically, when the number of earnings announcements in the analysts' coverage portfolio increases by one unit, the probability to issue a timely forecast decreases by 1.7 pp. Analysts are more likely to issue timely forecasts for firms with higher institutional ownership, which means they cater to institutional clients and immediately respond to earnings announcements of firms with higher institutional ownership. When the analysts follow more firms or have more experience in issuing forecasts for the firm, they are more likely to issue timely forecasts.

By studying the effect within analysts and within firm-quarter, the above baseline analysis provides strong evidence that female analysts' forecast timeliness is significantly influenced by the increase in domestic burdens caused by the COVID-19 school closures. To further check the robustness of the results, I define the counterfactuals in different ways.

To start with, I use a shorter time window in March 2020 and conduct similar analyses. In this way, the model emphasizes the staggered feature in school closure decisions across states in March 2020. The number of observations in this sample significantly drops to 1698. Columns (1) and (2) in Table 4 contain the regression results. In line with previous findings, school closure reduces female analysts' forecast more than that of male analysts: the around 10 pp difference, which is statistically significant at the 10% level, accounts for 13.5% of the average probability to issue a timely forecast in the sample (Table 1). The effect of school closures on the forecast timeliness among male analysts (6.3 pp in Column (2) of Table 4) is not statistically significant at the 10% level. The estimated gender difference in this sample is larger than that in the sample from January 2020 to August 2020. The attenuation in the economic size of the school closure effect may be due to potential confounding factors in a larger time window. It is also possible that analysts are able to deploy strategies to deal with the increase in childcare demand over time, and therefore, the effect of school closures on forecast timeliness in March is mitigated in an extended window.

Analysts' forecasts before and after school closures are issued at different time of a year. Lo and Wu (2018) and Chang et al. (2017) find that analysts' forecasts are influenced by the seasonality. To take out the seasonality of the analysts' forecasts, I compare the earnings forecasts after the earnings announcements from March 23rd to August 31st in 2020 when most schools in all states are closed during the COVID-19 pandemic with those in the same time period in the previous year 2019. In other words, the sample is from March 23rd to August 31st in 2019 and 2020, and *School closure* is defined as equal to one, if the earnings forecast is issued in the year 2020, and zero otherwise. Results in columns (3) and (4) of Table 4 confirm that school closures have a negative effect on female analysts' forecast timeliness.

3.2 The impact of gender attitude

The observed gender difference in the effect of the COVID-19 school closures on forecast timeliness may be due to reasons other than the gender inequality in housework allocation. For example, if female analysts spend a longer time in analyzing information to issue earnings forecasts during a pandemic or a recession caused by the pandemic because women are more risk-averse (e.g., Powell and Ansic (1997)) and less overconfident (e.g., Lenney (1977) and Barber and Odean (2001)), the findings in the previous section may be explained by the nature of gender differences rather than the unequal division of domestic work. However, the channel of gender differences in response to pandemics is not likely to exist because female analysts are more competitive and better educated than male analysts (Kumar (2010) and Fang and Huang (2017)). Studies have found that gender differences in risk aversion and overconfidence are much smaller after controlling for knowledge and self-selection (Dwyer et al. (2002) and Hardies et al. (2013)).

To further confirm the explanation of distractions of the childcare demand, I explore the cross-sectional difference in the division of household responsibilities across states. Social environment shapes people's values, beliefs, and behavior (e.g., Kumar et al. (2011)). The sexual division of labor at home is likely to be more imbalanced in states with conservative gender attitudes (Ruppanner and Maume (2016)), and analysts may conform to expectations of the local social environment.[14] Therefore, I expect the observed gender difference in the effects of the COVID-19 school closures on forecast timeliness is larger among states with conservative gender attitudes.

I use the U.S. 2017 wave of the World Value Survey to calculate a gender attitude index for each state as the average of three measures on gender attitude from questions about opinions on women in jobs, political positions, and education for all respondents from each state, following the way the World Value Survey calculates the gender attitude index for each country.[15] Internet Appendix Figure IA2 shows the cross-sectional variation of gender attitude across states in the U.S. I divide states into liberal- or conservative- gender-attitude states with this measure. $Liberal_j$ is a dummy variable equal to one, if the gender attitude index is larger or equal to the median in the sample, i.e., the gender attitude index of New York at 0.724, and zero otherwise. Table 1 shows that 82% of the analysts in the sample are located in states with liberal gender attitudes because more than half of the analysts are located in New York, where the gender attitude is relatively liberal .

[14] Previous studies have used firms' local social environment as a proxy to examine CEOs' behavior, see, e.g., Hilary and Hui (2009) and Focke et al. (2017).

[15] I use the arithmetic mean of the measures across all respondents from the same states. Using weighted means with the sample weight from the survey does not materially change the state-level measure.

Table 5 presents the regression results in sub-samples of states with liberal or conservative gender attitudes. The coefficient estimate of the interaction term between *Female* and *School closure* is statistically insignificant in states with liberal gender attitudes but is statistically significant at the 10% level and economically large (13 pp) in states with conservative gender attitudes in the model with firm, broker, state, and time fixed effects (columns (1) and (2)). In the model controlling for analyst, firm, and time fixed effects (columns (3) and (4)), the gender difference in the effect of the school closures on the forecast timeliness increases to 6 pp and becomes statistically significant at the 5% level in states with liberal gender attitudes. The gender difference is much larger at 11.5 pp in states with conservative gender attitudes, which is statistically significant at the 10% level.

Indeed, school closures influence female analysts more in states with conservative gender attitudes. The results further confirm that the gender difference in the effect of school closures on forecast timeliness comes from the unequal allocation of domestic work between gender. Other channels such as gender differences in risk-aversion cannot explain the different findings in liberal and conservative states in terms of gender attitudes.

3.3 Placebo tests using financial crises

The time of COVID-19 school closures overlaps with a financial crash. Is it possible that female analysts' forecast timeliness is negatively influenced by the financial crash? As discussed previously, it is possible that female analysts are more risk-averse and less overconfident and thus, may be more likely to postpone the forecast release during financial crises. In this section, I conduct a placebo test on the gender difference in forecast timeliness during financial crises.

Based on the NBER definition of the financial crisis, there are two financial crises from 1999 to 2020 (restricted by the I/B/E/S sample): one from March 2001 to November 2001 and the other from December 2007 to June 2009. To have an approximately symmetric window around each financial crisis, I use the sample period from 2000 to 2002 and the sample period from 2007 to 2010, respectively. Table 6 presents the results. The financial crisis in 2001 does not have a significant effect on forecast timeliness while the more severe financial crisis in 2008 decreases the likelihood to issue timely forecasts by more than 20 pp. In contrast to the gender difference in the negative effect of the school closures on forecast timeliness, the negative effect of the 2008 financial crisis is not more salient among female analysts. If there is anything in gender difference, female analysts are even 1.8 pp more likely to issue timely forecasts during the 2008 financial crisis, but the effect becomes insignificant once the firm-quarter fixed effects and analyst fixed effects are controlled for.

3.4 Evidence from H1N1 school closures

Another massive school closure event in the U.S. happened during the H1N1 pandemic, commonly referred to as "swine flu", in 2009. However, it is hard to capture the effect of the school closure event in 2009 because the decisions on school closures were inconsistent and dispersed (Klaiman et al. (2011)), unlike the school closure decisions during the COVID-19 pandemic.[16] I try to capture the effect of school closures in two ways. First, I compare the forecast timeliness in 2009 with that in the previous and subsequent years 2008 and 2010. H1N1-related school closures happened

[16] The U.S. Centers for Disease Control and Prevention (CDC) recommended school closures on May 1st, 2009 but quickly revised its recommendation on May 5th, 2009 to not closing the school but keeping ill children home.

at different times across the year 2009, i.e., both in spring when the pandemic started and in fall during the second wave. Therefore, comparing the forecast timeliness in 2009 with that in 2008 and 2010 may capture the aggregated effect of school closures in 2009, given that there is no massive school closure event in 2008 and 2010. In addition, I take advantage of the fact that New York continued school closures even after the CDC ceased recommending school closures, and other states opened schools (Klaiman et al. (2011)), comparing the difference in forecast timeliness between New York analysts and non-New York analysts in May and June 2009.

Table 7 contain the regression results. Female analysts are 2 pp less likely to issue timely forecasts in 2009 when school closures happened, compared with the forecasts in 2008 and 2010. In May and June 2009, in New York where many schools were still closed, the gender difference in the probability to issue timely forecast is 6.9 pp lower than that in states where schools were not ordered to close. The effect is statistically significant at the 5% level without control variables in the model (Column (3)) and is economically significant, amounting to 88% of the gender difference in forecast timeliness of analysts in states other than New York. The effect becomes statistically significant at the 10% level when control variables are added, but the economic level remains similar (Column (4)).

To summarize, female analysts are less likely to issue timely forecasts after unexpected school closures caused by pandemics, but there is no significant gender difference in forecast timeliness during financial crises. School closures increase the demand for domestic work and childcare, leading to less timely forecasts of female analysts. According to previous literature (Cooper et al. (2001), Zhang (2008), Chiu et al. (2021)), less timely forecasts are associated with smaller market impact and less favorable career outcomes, making it harder for female analysts to succeed in this competitive industry.

4 Child-rearing and effect of school closures on forecast timeliness

The analyses so far compare the effect of the COVID-19 school closures on the forecast timeliness of male and female analysts, independently of whether they have children or not.[17] The comparison of forecast timeliness in the sample pooling analysts with and without children may underestimate the treatment effect, potentially giving rise to attenuation bias, because child-rearing duties are critical for the effect.

To further attribute the effect of the COVID-19 school closures on forecast timeliness to the distractions caused by school closures, I collect data on family conditions of analysts by checking their Facebook page. Internet Appendix I describes the detailed process of the data collection. I find Facebook pages for 680 analysts and 290 of these pages contain photos of the analysts' children.[18] I then estimate the children's ages based on the photos and the time of the posts. 262 out of the 290 analysts who have posted photos of their children have at least one child under 18. Analysts whose children are all adults, whose Facebook posts do not have photos of their children, or whose Facebook pages cannot be found, are used as the control group. Note that it is possible that some analysts who have children do not post them on Facebook. This adds noise in the measure and

[17] Analysts are likely to be in the prime years of child-rearing, given that the average age in the financial analyst industry is around 40 years old. See `https://datausa.io/profile/soc/financial-analysts`.

[18] I identify whether the children in the photos are children of the analysts or, e.g., children of their friends or siblings, based on the texts and comments in the posts. Potential misattribution may add noise to the data, underestimating the treatment effect.

may even underestimate the treatment effect because some analysts in the control group may have children as well.

Figure 3 compares the coefficient estimates of *School closure* in the regression of *Timely* on *School closure* in sub-samples of male analysts with children, female analysts with children, and other male and female analysts, respectively. All regressions control for analyst fixed effects, and standard errors are clustered by analyst and firm. School closures have a negative impact on forecast timeliness of all analysts, but the magnitude of the effect substantially differs across different groups of analysts. School closures decrease the forecast timeliness of female analysts with children by 14 pp and that of male analysts with children by only 2 pp. The effects of school closures on the forecast timeliness of other analysts in the sample has a modest gender difference, i.e., 4 pp for male analysts and 5 pp for female analysts. The decrease in forecast timeliness of female analysts with children amounts to 7 times of the decrease in forecast timeliness of male analysts with children and around 3 times of the decrease in forecast timeliness of other male and female analysts.

Information on whether an analyst has a non-adult child refines the definition of the treatment and control groups. Analysts with children are in the treatment group whereas other analysts are in the control group. Moreover, analysts are subdivided based on their gender within each group because domestic burdens increased by school closures are expected to have a larger impact on female analysts.

To start with, I compare female analysts with children with other female analysts by running a regression of *Timely* on *School closure*, *Having children*, and their interaction term. *Having children* is a dummy variable equal to one if an analyst's Facebook page contains photos of her non-adult children, and zero otherwise. This sample consists of female analysts only, ruling out other explanations related to gender differences. Panel A of Table 8 contains the regression results. Column (1) presents the model controlling for analyst fixed effects. The result shows that the around 9 pp difference in the effects of school closures on female analysts with children and other female analysts is statistically significant at the 10% level. After including control variables and analyst, firm, and time fixed effects (Column (2)), female analysts with children are 13.1 pp less likely to issue timely forecasts after school closures than other female analysts, and the result is statistically significant at the 5% level. By contrast, in columns (3) and (4), I compare the forecast timeliness of male analysts with children and that of other male analysts but do not find any significant result.

The comparison within female analysts would be invalid to establish causality if there is a contemporaneous shock, other than the COVID-19 school closures, that affects all analysts with children. This is very unlikely to happen, given the staggered nature of school closures across states. To still address this issue, another option to establish a counterfactual is to compare the gender difference within analysts with children. Panel B of Table 8 contains the regression results of *Timely* on *School closure*, *Female*, and their interaction term in the sub-samples of analysts with children or other analysts. The results show that the forecast timeliness of mothers decreases by 12.3 pp or 22.8 pp more after school closures, compared with that of fathers (columns (1) and (2)). By contrast, there is no gender difference in the effect of school closures on forecast timeliness in the sample of analysts who do not have non-adult children based on the Facebook data (columns (3) and (4)).

Finally, the setting allows conducting a triple difference or difference-in-difference-in-differences (DDD) analysis (e.g., Gruber (1994)), which uses higher-order contrast to draw causal inference (Angrist and Pischke (2008)). I conduct the triple difference estimation by adding interaction terms among *School closure*, *Having children*, and *Female* in the model of Equation 1. Panel C of Table 8 shows the results. The distraction of domestic burdens caused by school closures decreases mother analysts' forecast timeliness by 11.0–14.9 pp, which accounts for up to 20% of the average forecast timeliness in the sample. This effect estimated by the coefficient estimates of the triple interaction term is statistically significant at the 5% level in all model specifications.

Information from analysts' Facebook pages further confirms that analysts distracted by domestic burdens are less likely to issue timely forecasts. The data collected from Facebook may have limitations because it solely relies on public posts by analysts. Male analysts may be less likely to have Facebook pages or less likely to post photos of their children, compared with female analysts.[19] This would bias the results if male analysts who have posted photos of their children are less likely to be influenced by school closures than male analysts who have children but do not post them on Facebook. However, this is implausible because people who spend time in taking care of their children are expected to be more likely to post photos of children on social web pages.

[19]Table 2 shows that slightly more female analysts are identified as having children. The reason is that more female analysts' Facebook pages are found (see Internet Appendix I for more details).

5 Additional analyses on analyst activities after the COVID-19 school closures

5.1 Forecast release time

If female analysts get distracted by the increase in domestic burdens after the COVID-19 school closures, the time of day to release forecasts may be significantly influenced. For example, analysts may need to take care of the children and cook meals during daytime and therefore, have to issue forecasts at night when the children go to sleep. Analysts have busy daily schedules (Bradshaw et al. (2017)) and may strategically choose the time of day when they release earnings forecasts. However, very little is known about what influences the time of day when analysts issue forecasts.

This section investigates the effect of the COVID-19 school closures on the forecast release time. The forecast release time is obtained from the I/B/E/S database.[20] I transfer the data based on Eastern Standard Time zone to local time based on the state where the analyst locates.[21]

Figure 4 plots the distribution of the forecast release time of the day, separately, for male and female analysts before and after the school closures. The bright histogram draws the distribution of forecast release time before school closures whereas the dark histogram draws the distribution of forecast release time after the school closures. As expected, after school closures, the fraction of forecasts released by female analysts increases during most hour intervals at night (from 21:00

[20]Based on the interpretation by the data provider, the variable announcement time (ANNTIMS) from IBES Detail History file is the time when a broker's estimate is being released to I/B/E/S. It may be obtained via research reports or via earnings feeds. The time stamp "00:00:00" may be missing values, so I exclude the observations (only 133) from the sample.

[21]I refer to Wikipedia page on the U.S. time zone: `https://simple.wikipedia.org/wiki/List_of_U.S._states_and_territories_by_time_zone`. Some states have more than one time zones and the time zone of the largest part of the territory in the state is used. For example, some counties near the southwestern and northwestern border of Indiana use Central Standard Time but I assume Indiana uses Eastern Standard Time.

to 4:00 of the next day) but decreases during the day and in the evening. By contrast, the change in the forecast release time for male analysts after school closures is visually smaller, even though there is a similar pattern that more forecast releases happen at night rather than during daytime.

In the next step, I formally test whether female analysts are less likely to release forecasts during the periods of a day when housework is intensive in regressions with control variables and fixed effects. I define *Housework-intensive time* as a dummy variable equal to one, if analyst j releases the earnings forecast for firm i during the time period of a day when housework demand such as cooking and childcare is high, i.e., in the morning from 7:00 to 9:00, at noon from 12:00 to 14:00, and from 17:00 to 21:00 in the evening, and zero otherwise.

Based on the summary statistics in Table 1, 34% of the analyst forecasts in the sample is released during the housework-intensive. I run a regression of *Housework-intensive* on *Female*, *School closure*, and their interaction term, controlling for firm, broker and state (or analyst), and time fixed effects. I include analyst characteristics, the number of firms in the coverage, broker size and analysts' experience in the firm, because these characteristics may influence the time of day an analyst releases forecasts. Table 9 contains the regression results. After school closures, female analysts are 9 pp less likely to release forecasts during housework-intensive hours. On the contrary, male analysts do not significantly shift the time of day when they release forecasts.

To have a closer look at how analysts shift their forecast releasing time, I run regressions of dummy variables indicating whether the forecast is released during the hour of the day on the school closure dummy in the sample of male analysts' forecasts and female analysts' forecasts, separately. The regressions control for analyst fixed effects to focus the within-analyst change in the forecast time, and the standard errors are clustered by analyst. Figure 5 contains the coefficient estimates of the school closure dummy for each time interval. The confidence intervals of coefficient estimates plotted are at the 90% level. Female analysts are less likely to release forecasts at noon from 12:00-14:00 and are more likely to release forecasts from 21:00-22:00 after school closures. By contrast, the change of likelihood to release forecasts during these time intervals for male analysts does not differ from zero. In general, I observe the pattern that the change in the release time for female analysts is economically larger than that for male analysts. However, the gender difference may not be statistically significant at the conventional level. The small number of female analysts leads to a large standard deviation of the coefficient estimates while the standard deviation of the coefficient estimates in the sample of male analysts is much smaller.

Taking advantage of the detailed time stamp of analysts' forecasts, I show that female analysts shift the forecast releases to hours when childcare activities and housework demand are less intensive. This result provides additional evidence that the COVID-19 school closures have a larger impact on female analysts' attention at work because women take more responsibilities for childcare.

5.2 Forecast boldness and accuracy

Widely studied by the previous literature, forecast boldness and forecast accuracy are important perspectives of the quality of analyst earnings forecasts. Unlike the effect of school closures on forecast timeliness, how limited attention influences forecast boldness and forecast accuracy is less clear. On the one hand, when distracted by domestic burdens, analysts may be more likely to herd and issue a forecast similar to that of other analysts or her previous forecasts. On the other hand, analysts may be less likely to pay attention to all available information including the forecasts by other analysts, and issue a forecast deviating more from the consensus after school closures. Furthermore, forecast boldness and forecast accuracy may represent analysts' capability to gather and interpret information and thus, may not be influenced by an exogenous distraction. Analysts can also choose to delay the forecast releases in order to guarantee the forecast boldness and accuracy (Clement and Tse (2003), Guttman (2010), and Shroff et al. (2014)). In this section, I empirically investigate whether and how the forecast boldness and accuracy are influenced by the school closures.

To define measures of forecast boldness, I first calculate the distance between a given forecast and the consensus of all forecasts for the firm-quarter (measured as the average of all available analyst earnings forecast values for the same firm-quarter) at the time of the analyst forecast release. Another measure is the distance between a given forecast and the previous forecast of the analyst for the firm-quarter. To get the consensus of the forecast and the analyst's previous forecast, I use a sample of all earnings forecasts 360 days before a firm's earnings announcement dates. I calculate variables *Distance from consensus* and *Distance from previous* with the following equation (Clement and Tse (2005)):

$$Distance_{i,j,t} = \frac{Absolute\,distance_{i,j,t} - Absolute\,distance\,Min_{i,t}}{Absolute\,distance\,Max_{i,t} - Absolute\,distance\,Min_{i,t}}, \quad (2)$$

where $Absolute\,distance_{i,j,t}$ is the absolute value of the difference between the analyst forecast value and the consensus of analyst forecasts or the previous forecast issued by the same analysts; $Absolute\,distance\,Min_{i,t}$ and $Absolute\,distance\,Max_{i,t}$ are the minimum and the maximum of $Absolute\,distance_{i,j,t}$ for firm i in quarter t. The boldness measures vary from 0 to 1, and the higher the score is, the bolder the analyst's forecast is, comparing within the forecasts for the same firm-quarter.

As for forecast accuracy, I first calculate the forecast error as the absolute value of the difference between the analyst earnings forecast and the actual earnings announced by the firm. The larger the forecast error is, the less accurate the forecast is. To better capture the change in information, I follow Keskek et al. (2014) and define *Accuracy improvement* as a dummy variable equal to one, if a forecast is more accurate than the most recent forecast by another analyst, and zero otherwise. Additionally, following Clement and Tse (2005), I define *Forecast accuracy* as:

$$(3) \qquad Forecast\, accuracy_{i,j,t} = \frac{Forecast\, error\, Max_{i,t} - Forecast\, error_{i,j,t}}{Forecast\, error\, Max_{i,t} - Forecast\, error\, Min_{i,t}},$$

where $Forecast\, error\, Min_{i,t}$ and $Forecast\, error\, Max_{i,t}$ are the minimum and maximum of the forecast errors (an absolute value) for all analysts following firm i in quarter t issued in the same calendar month. $Forecast\, accuracy_{i,j,t}$ varies from 0 to 1, and the larger the value is, the more accurate the analyst's forecast is, comparing within the forecasts for the same firm-quarter issued in the same month.

In the next step, I run a regression of the forecast boldness and accuracy measures on the dummy variables *Female*, *School Closure*, and their interaction terms, controlling for firm and analyst characteristics. I further include analyst and time fixed effects. Standard errors are clustered by analyst and firm.

Table 10 contains the regression results. I find some evidence that female analysts' forecasts deviate more from the consensus forecasts after school closures. The effect amounts to 6.4 pp, which is statistically significant at the 5% level. Female analysts' forecasts deviate slightly more from their own previous forecasts as well, but the effect is not statistically significant. Female analysts issue forecasts that deviate more from the consensus but do not deviate more from their own previous forecasts, so a potential explanation could be that they do not pay as much attention to available forecasts by other analysts as they did before school closures.

Regarding the results on forecast accuracy in columns (3) and (4), school closures decrease the probability of female analysts improving the forecast accuracy relative to the most recent forecast by 2.7 pp, and decrease the relative measure of forecast accuracy by 3.6 pp. However, these effects are not statistically significant. I do not find strong evidence that female analysts issue less accurate forecasts after the COVID-19 school closures. Forecast accuracy represents analysts' capability that may not be easily changed by limited attention.

5.3 Analysts' activities at earnings conference calls

At last, I investigate analysts' activities at earnings conference calls. If analysts are distracted by the COVID-19 school closures, their activities at the conference call may also be influenced and the effect is expected to be larger among female analysts. I conjecture that female analysts may be less likely to ask questions in conference calls after school closures. In addition, female analysts who participate in earnings conference calls may ask shorter and fewer questions.

I construct a sample consisting of conference call transcripts for earnings conference calls from January 2020 to August 2020. The conference call transcripts are obtained from Seeking Alpha. I extract the analysts' names from the transcripts and match them with the analysts that issue forecasts for the firm in the quarter based on the I/B/E/S database. Internet Appendix Section II contains the analyses and results in details.

I do not find significant effect of the COVID-19 school closures on the participation of conference calls for either male or female analysts. Nevertheless, female analysts are less likely to ask questions during some time of the day after the COVID-19 school closures, more specifically, from 5:00 to 6:00 in the morning and from 11:00 to 12:00 at noon (Internet Appendix Figure IA3). Furthermore, conditional on participating in the conference, female analysts ask shorter and fewer questions after the COVID-19 school closures (Internet Appendix Table IA5).

6 Conclusion

In this paper, I find strong and robust evidence that the COVID-19 school closures negatively influence the forecast timeliness of female analysts, especially in states where the general gender attitudes are conservative. Conducting a triple difference analysis with manually-collected data, I estimate a 15 pp decrease in mother's forecast timeliness after the COVID-19 school closures. Female analysts shift the forecast release time to hours without intensive housework after the school closures. I find some evidence that the school closures influence female analysts' activities at conference calls as well.

Even though female analysts are competitive women who choose and survive in this male-dominated industry, they are still more likely to be influenced by domestic responsibilities when the demand for childcare unexpectedly increases after the COVID-19 school closures. Consistent with the sexual division of labor theory by Becker (1985), the gender imbalance in childcare duties and domestic tasks may at least partially explain the notable unrepresentativeness of women and the existing gender pay gap in competitive industries. On the bright side, the findings also imply that the gender gap in the job market may be able to get closed by alleviating the imbalance in housework allocation between gender or by providing better external childcare services.

To my knowledge, this paper is the first to link distractions of domestic work to analysts' forecasts and the labor market of the financial analyst industry. Even professional analysts are influenced by distractions of housework. It is likely that other financial market participants also suffer from limited attention due to distractions of domestic burdens, and the effect may have a large impact on financial markets. This study serves as a starting point for future research to quantify and investigate the effect of domestic duties on financial markets.

The findings also add to the increasing understanding of the social effects of the COVID-19 pandemic. COVID-19-induced measures such as school closures decrease forecast timeliness of female analysts, which influence information processing efficiency in financial markets. More importantly, it should be brought to the attention of policymakers that these measures influence different groups in an unequal way. As found in this paper, even women in a competitive profession are more vulnerable to the COVID-19-related social effects.

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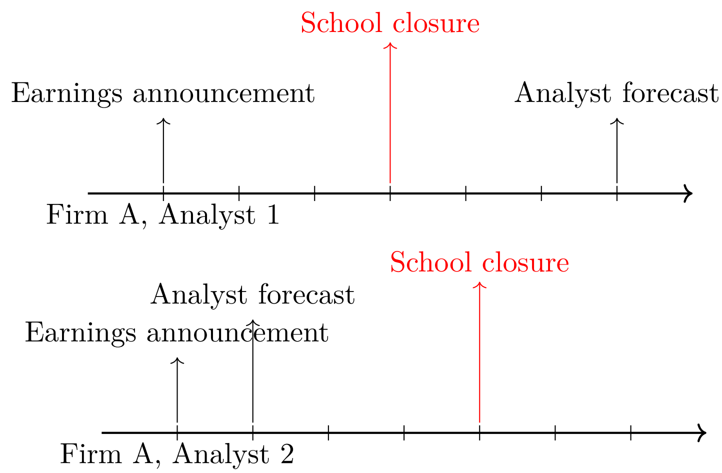
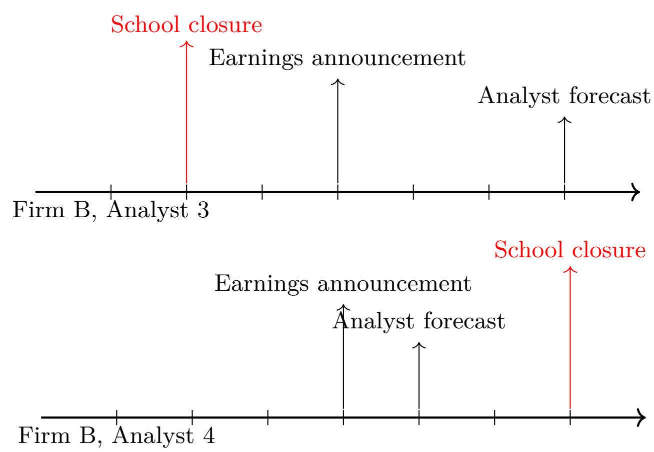
Figure 1: Demonstration of the sample construction

This figure demonstrates the sample construction. Scenario 1 demonstrates earnings announcements excluded from the sample where earnings announcements happened before school closures in a state, and a forecast of an analyst in that state was issued after school closures. Scenario 2 demonstrates earnings announcements not excluded from the sample where both earnings announcements and analyst's forecasts happened before or after the school closure.



Scenario 1



Scenario 2

Figure 2: Forecast timeliness of male and female analysts' earnings forecasts around the COVID-19 school closures

This figure plots the average probability to issue timely forecasts among male analysts and female analysts four weeks before and four weeks after the COVID-19 school closures.

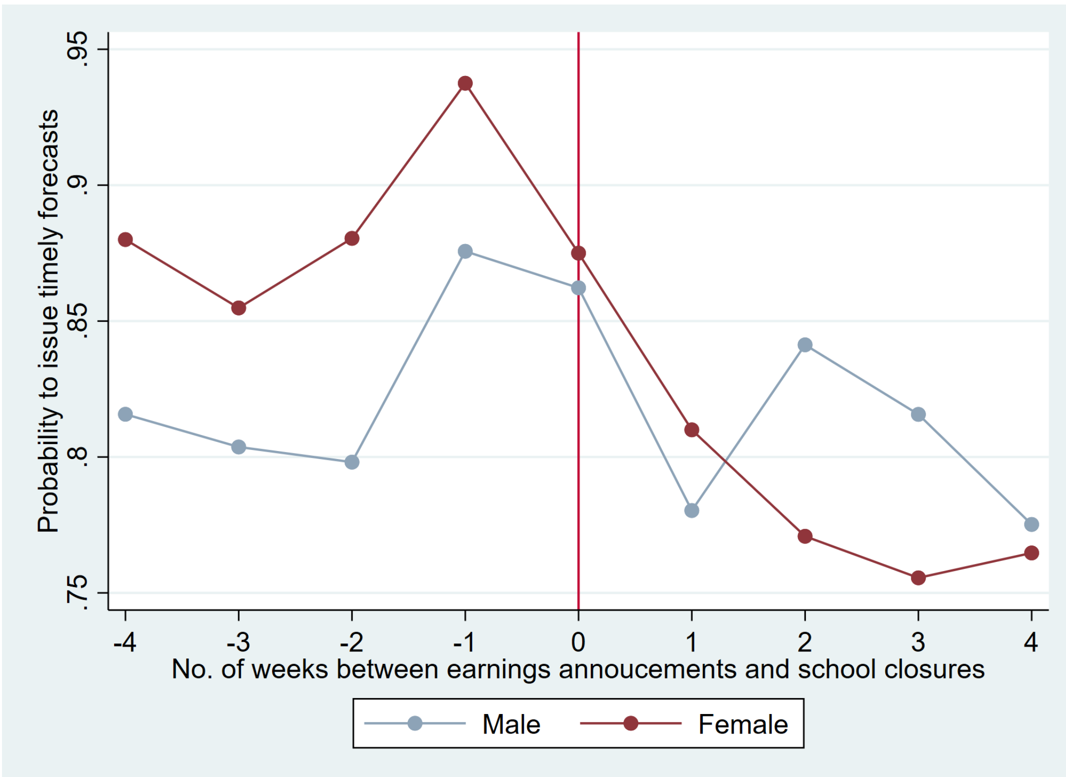


Figure 3: School closures effects on forecast timeliness among analysts

This figure plots the coefficient estimates of *School closure* in the regression of *Timely* on *School closure* in sub-samples of male analysts and female analysts with children based on the information from their Facebook, and male analysts and female analysts in the rest of the sample. The models control for analyst fixed effects. Standard errors are clustered by analyst and firm. The confidence intervals of the coefficient estimates are at the 90% level.

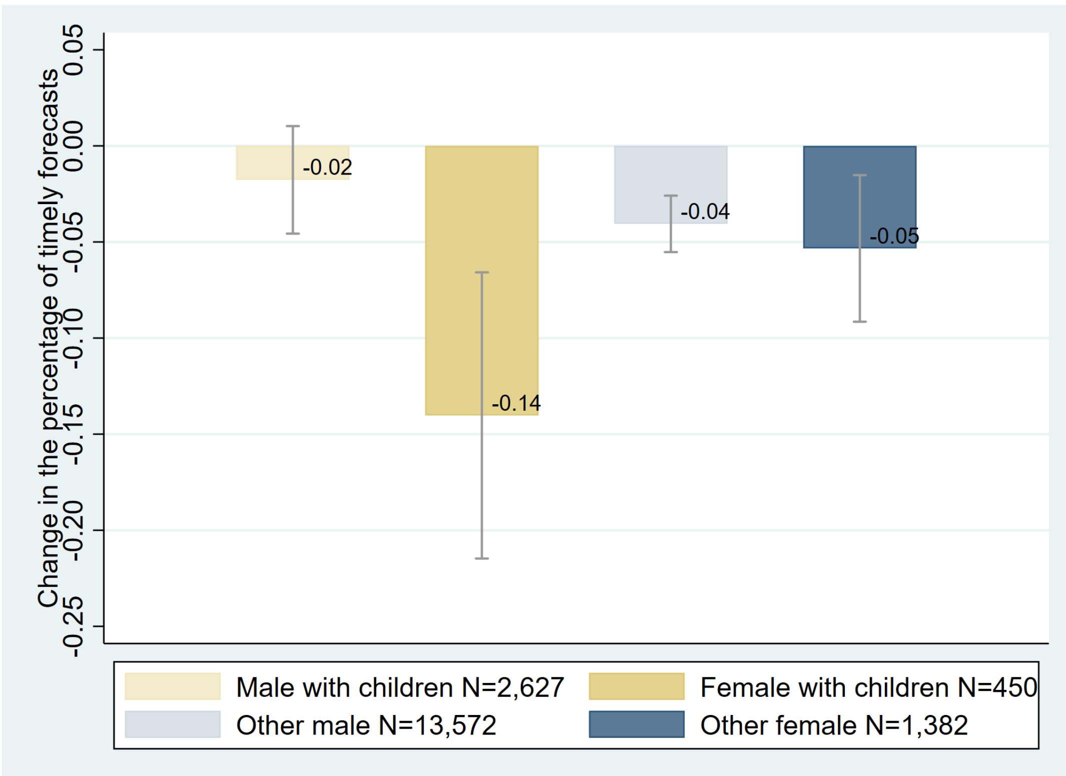


Figure 4: COVID-19 school closures and distribution of forecast release time

This figure plots the fraction of earnings forecasts released by male and female analysts during each time period of the day before and after the COVID-19 school closures. The bright histogram draws the distribution of forecast release time before school closures, and the dark histogram draws the distribution of forecast release time after school closures.

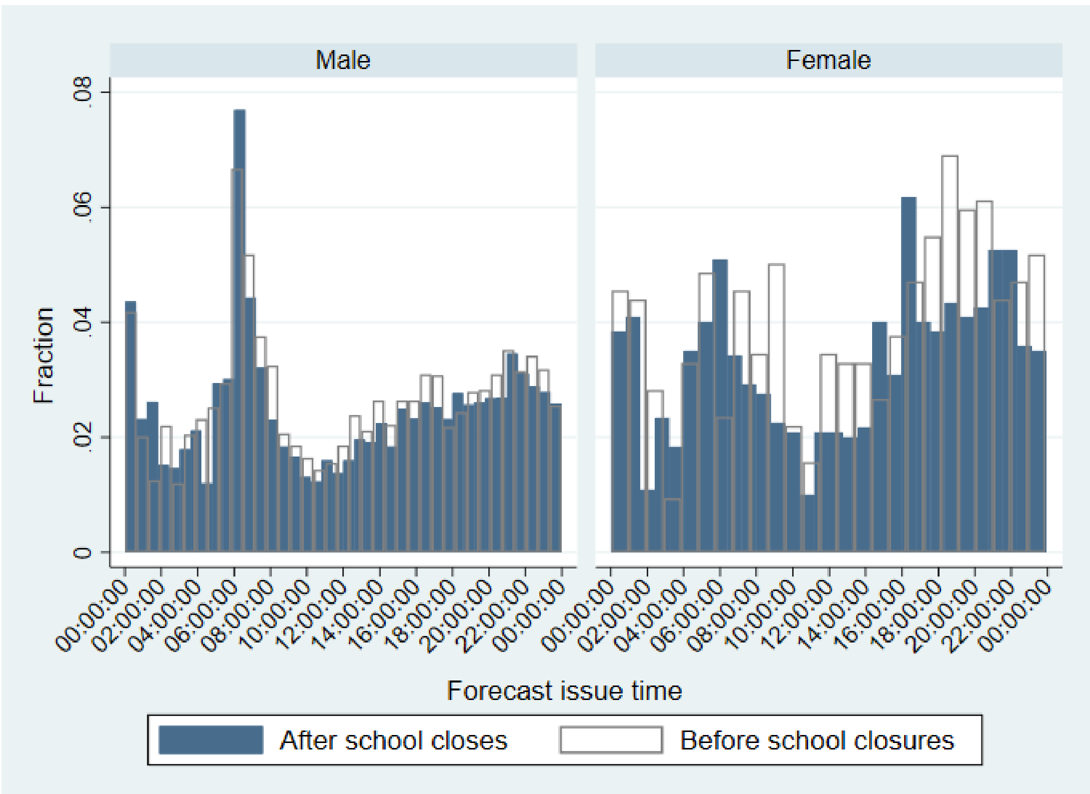


Figure 5: Effect of school closures on forecast release time among male and female analysts

This figure plots the coefficient estimates of *School closure* in the regressions of dummy variables indicating whether the forecast is released during the hour of the day on the dummy variable *School closure* in the sub-samples of male analysts' forecasts and female analysts' forecasts. The regressions control for analyst fixed effects, and the standard errors are clustered by analyst. The confidence intervals of the coefficient estimates are at the 90% level.

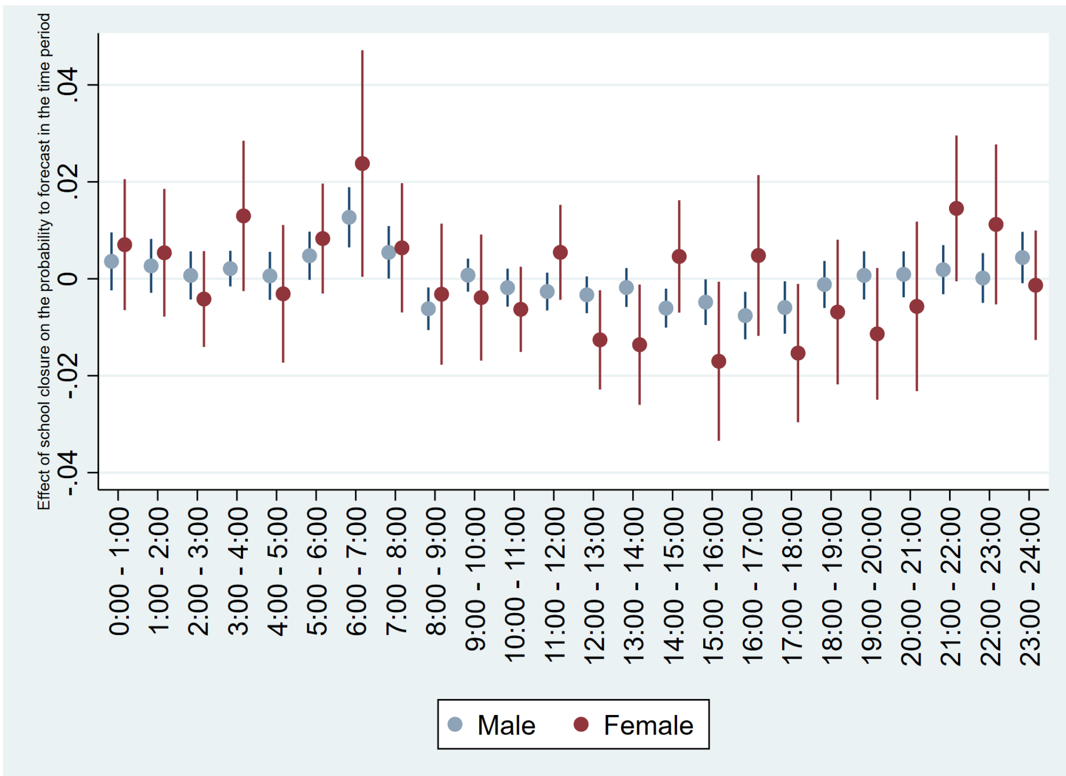


Table 1: Summary statistics

This table contains summary statistics, including the number of observations (Obs), mean, standard deviation (Std. Dev.), 25% percentile (P25), median, and 75% percentile (P75), for a sample of the first forecast by each analyst for a firm's earnings in quarter t+1 issued after the firm's quarter t earnings announcement but before one day prior to quarter t+1 earnings announcement from January 2020 to August 2020. Earnings announcements are excluded from the sample if earnings announcements happened before school closures in a state, and a forecast of an analyst in that state was issued after school closures. The variables are at the firm-quarter-analyst level. All variables are defined in Appendix B.

Variable	Obs	Mean	Std. Dev.	P25	Median	P75
Female	18701	0.10	0.30	0.00	0.00	0.00
School closed	18172	0.64	0.48	0.00	1.00	1.00
Timely	18701	0.74	0.44	0.00	1.00	1.00
Liberal	18701	0.82	0.38	0.00	1.00	1.00
Having children	18701	0.17	0.37	0.00	0.00	0.00
Housework-intensive time	18064	0.34	0.47	0.00	0.00	1.00
Distance from consensus	17853	0.45	0.35	0.12	0.40	0.77
Distance from previous	16156	0.46	0.36	0.14	0.42	0.78
Accuracy improvement	18038	0.54	0.50	0.00	1.00	1.00
Forecast accuracy	15491	0.54	0.37	0.19	0.59	0.91
No. of followed firms' EA	18701	0.82	1.21	0.00	0.00	1.00
No. of firms followed	18292	18.28	7.93	13.00	18.00	23.00
Broker size	18292	45.55	31.69	19.00	41.00	63.00
Experience in the firm	18584	22.85	23.28	6.00	15.00	33.00
Firm size	17389	14.72	2.70	13.44	14.98	16.52
Institutional ownership	18322	0.69	0.26	0.54	0.76	0.89
Book to market	16345	0.55	0.48	0.21	0.42	0.77
Bad earning news	18634	0.35	0.48	0.00	0.00	1.00
Special items	16384	0.65	0.48	0.00	1.00	1.00
Log number of following analysts	18641	2.54	0.60	2.08	2.56	3.00

Table 2: Difference between male and female analysts

This table contains the difference in the value of main variables and control variables for male and female analysts in the sample from January 2020 to August 2020. Earnings announcements are excluded from the sample if earnings announcements happened before school closures in a state, and a forecast of an analyst in that state was issued after school closures. t-statistics are based on univariate regressions of the variables on the female dummy, and standard errors are clustered by analyst and firm. All variables are defined in Appendix B.

	Male	Female	Diff	t-statistics
Timely	0.735	0.773	-0.038	-1.84
Liberal	0.824	0.877	-0.054	-1.45
Having children	0.157	0.229	-0.072	-1.60
Housework-intensive time	0.334	0.363	-0.029	-1.53
Distance from consensus	0.451	0.467	-0.016	-1.29
Distance from previous	0.463	0.476	-0.013	-1.03
Accuracy improvement	0.542	0.524	0.018	1.34
Forecast accuracy	0.545	0.515	0.030	2.37
No. of followed firms' EA	0.813	0.856	-0.043	-0.40
No. of firms followed	18.337	17.815	0.522	0.68
Broker size	44.854	51.702	-6.848	-2.11
Experience in the firm	22.993	21.632	1.360	0.88
Firm size	14.712	14.769	-0.057	-0.50
Institutional ownership	0.694	0.683	0.011	0.08
Book to market	0.546	0.559	-0.013	-0.44
Bad earning news	0.343	0.362	-0.019	-1.02
Special items	0.658	0.596	0.062	3.19
Log number of following analysts	2.536	2.532	0.004	0.09

Table 3: Effect of COVID-19 school closures on forecast timeliness

This table contains the regression results of *Timely* on *Female*, *School closure* and their interaction term. *Timely* is a dummy variable equal to one, if the analyst issues an earnings forecast for quarter t+1 within one trading day (day 0 or day 1) after the firm's quarter t earnings announcement date, and zero otherwise. All variables are defined in Appendix B. Standard errors are clustered by analyst and firm. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:		Timely	
	(1)	(2)	(3)
Female × School closure	-0.043*	-0.067***	-0.062***
	(-1.67)	(-2.66)	(-2.59)
School closure	-0.064**	-0.031	-0.036
	(-2.31)	(-1.01)	(-1.15)
Female	0.049**		
	(2.11)		
No. of followed firms' EA	-0.017***	-0.017***	-0.016***
	(-3.48)	(-4.11)	(-3.84)
Firm size	0.012	0.012*	
	(1.60)	(1.89)	
Institutional ownership	0.043*	0.046**	
	(1.75)	(2.04)	
Book to market	0.013	0.019	
	(0.41)	(0.66)	
Bad earning news	-0.010	-0.011	
	(-0.60)	(-0.73)	
Special items	0.019	0.007	
	(0.34)	(0.13)	
Log number of following analysts	0.074	0.032	
	(0.91)	(0.40)	
No. of firms followed	0.004***	0.003	0.003
	(5.57)	(1.07)	(1.00)
Broker size	0.001	-0.001	-0.000
	(0.75)	(-0.34)	(-0.22)
Experience in the firm	0.0005**	0.0004*	0.0004*
	(2.33)	(1.78)	(1.74)
Fixed effects	Firm, Broker, State, Time	Firm, Analyst, Time	Firm-quarter, Analyst, Time
Observations	15208	15378	15347
Adjusted R^2	0.292	0.428	0.429

Table 4: Effect of COVID-19 school closures on forecast timeliness – Other counterfactuals

This table contains the regression results of *Timely* on *Female*, *School closure* and their interaction term. Columns (1) and (2) run regressions in the sample of March 2020 and *School closure* is equal to one, if the state where the analyst is located has closed schools, and zero otherwise. Columns (3) and (4) run regressions in the sample from March 23rd to August 31st in 2019 and 2020 and *School closure* is equal to one, if the earnings forecast is issued in year 2020, and zero otherwise. *Timely* is a dummy variable equal to one, if the analyst issues an earnings forecast for quarter t+1 within one trading day (day 0 or day 1) after the firm's quarter t earnings announcement date, and zero otherwise. Control variables include *No. of followed firms' EA*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm.* All variables are defined in Appendix B. Standard errors are clustered by analyst and firm. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Timely			
	(1)	(2)	(3)	(4)
Counterfactual:	Across states in March 2020		2019 vs 2020	
Female × School closure	-0.093*	-0.122*	-0.039*	-0.048**
	(-1.86)	(-1.92)	(-1.67)	(-2.29)
School closure	-0.066*	-0.063		
	(-1.86)	(-1.26)		
Female	0.033		0.036**	
	(1.08)		(2.15)	
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Firm, Broker, State, Time	Firm, Analyst, Time	Firm, Broker, State, Time	Firm, Analyst, Time
Observations	1698	1337	42675	43613
Adjusted R^2	0.357	0.398	0.282	0.418

Table 5: Gender attitudes and the effect of school closures on forecast timeliness

This table contains the regression results of *Timely* on *Female*, *School closure* and their interaction term in separate samples of states with conservative or liberal gender attitudes measured by the US 2017 wave of the World Value Survey. *Timely* is a dummy variable equal to one, if the analyst issues an earnings forecast for quarter t+1 within one trading day (day 0 or day 1) after the firm's quarter t earnings announcement date, and zero otherwise. Control variables include *No. of followed firms' EA*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm*. All variables are defined in Appendix B. Standard errors are clustered by analyst and firm. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Timely			
	(1)	(2)	(3)	(4)
Gender attitudes:	Liberal	Conservative	Liberal	Conservative
Female × School closure	-0.028	-0.130*	-0.060**	-0.115*
	(-1.02)	(-1.85)	(-2.12)	(-1.67)
School closure	-0.031	0.000	0.019	
	(-1.07)	(0.00)	(0.61)	
Female	0.037	0.081		
	(1.54)	(1.30)		
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Firm, Broker, State, Time	Firm, Broker, State, Time	Firm, Analyst, Time	Firm, Analyst, Time
Observations	12244	2448	12142	2418
Adjusted R^2	0.287	0.367	0.421	0.424

Table 6: Effect of financial crises on the forecast timeliness – a placebo test

This table contains the regression results of *Timely* on *Female*, *Financial crisis* and their interaction term. Columns (1) and (2) run regressions in the sample from 2000 to 2002 and *Financial crisis* is equal to one if the earnings forecast is issued from March 2001 to November, 2001 based on the NBER financial crisis definition, and zero otherwise. Columns (3) and (4) run regressions in the sample from 2007 to 2010 and *Financial crisis* is equal to one if the earnings forecast is issued from December 2007 to June, 2009 based on the NBER financial crisis definition, and zero otherwise. *Timely* is a dummy variable equal to one if the analyst issues an earnings forecast for quarter t+1 within one trading day (day 0 or day 1) after the firm's quarter t earnings announcement date, and zero otherwise. Control variables include *No. of followed firms' EA*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm.* All variables are defined in Appendix B. Standard errors are clustered by analyst and firm. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Timely			
	(1)	(2)	(3)	(4)
Financial crisis:	2001		2007-2009	
Female × Financial crisis	0.007	0.008	0.018**	0.013
	(0.64)	(0.71)	(2.22)	(1.54)
Financial crisis	-0.023	-0.011	-0.277***	-0.229***
	(-1.64)	(-0.75)	(-13.69)	(-12.72)
Female	0.005		-0.007	
	(0.61)		(-0.66)	
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Firm, Broker, State, Time	Firm-quarter, Analyst, Time	Firm, Broker, State, Time	Firm-quarter, Analyst, Time
Observations	127681	152609	255772	288442
Adjusted R^2	0.198	0.308	0.243	0.331

Table 7: Effect of H1N1 school closures on the forecast timeliness

This table contains the regression results of *Timely* on *Female*, *H1N1 school closure* and their interaction term. Columns (1) and (2) run regressions in the sample from 2008 to 2010 and *School closure* is equal to one if the earnings forecast is issued in year 2020, and zero otherwise. Columns (3) and (4) run regressions in the sample of May and June 2020 and *School closure* is equal to one if the state where the analyst is located is New York, and zero otherwise. *Timely* is a dummy variable equal to one if the analyst issues an earnings forecast for quarter t+1 within one trading day (day 0 or day 1) after the firm's quarter t earnings announcement date, and zero otherwise. Control variables include *No. of followed firms' EA*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm*. All variables are defined in Appendix B. Standard errors are clustered by analyst and firm. *t*-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Timely			
	(1)	(2)	(3)	(4)
Counterfactual:	2009 vs 2008 and 2010		New York vs other states in May and June 2009	
Female × H1N1 school closure	-0.021**	-0.020**	-0.069**	-0.066*
	(-2.20)	(-2.15)	(-2.08)	(-1.95)
H1N1 school closure	0.079***	0.055***		
	(3.83)	(2.91)		
Female	0.008		0.078***	0.077***
	(0.72)		(2.84)	(2.76)
Control variables	Yes	Yes	No	Yes
Fixed effects	Firm, Broker, State, Time	Firm-quarter, Analyst, Time	Firm, Broker, State, Time	Firm, Broker, State, Time
Observations	190147	199488	8085	7563
Adjusted R^2	0.252	0.334	0.432	0.415

Table 8: Effect of COVID-19 school closures on parents' forecast timeliness

This table contains the regression results of *Timely* on *School closure*, *Female*, *Having Children* and their interaction terms. The information on whether an analyst has a non-adult child is manually collect from their Facebook pages. *Timely* is a dummy variable equal to one, if the analyst issues an earnings forecast for quarter t+1 within one trading day (day 0 or day 1) after the firm's quarter t earnings announcement date, and zero otherwise. Control variables include *No. of followed firms' EA*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm*. All variables are defined in Appendix B. Standard errors are clustered by analyst and firm. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Timely			
Panel A: Parent effect among female or male analysts				
	(1)	(2)	(3)	(4)
	Female		Male	
School closure × Having children	-0.087*	-0.131**	0.023	0.018
	(-1.78)	(-2.34)	(1.27)	(0.89)
School closure	-0.053**	-0.012	-0.041***	-0.062*
	(-2.32)	(-0.13)	(-4.55)	(-1.86)
Control variables	No	Yes	No	Yes
Fixed effects	Analyst	Firm, Analyst, Time	Analyst	Firm, Analyst, Time
Observations	1832	1240	16199	13969
Adjusted R^2	0.351	0.384	0.361	0.430
Panel B: Gender effect among parents or non-parents				
	(1)	(2)	(3)	(4)
	Parents		Other analysts	
School closure × Female	-0.123***	-0.228***	-0.013	-0.014
	(-2.61)	(-3.32)	(-0.53)	(-0.52)
School closure	-0.018	-0.132	-0.041***	-0.069*
	(-1.04)	(-1.41)	(-4.55)	(-1.90)
Control variables	No	Yes	No	Yes
Fixed effects	Analyst	Firm, Analyst, Time	Analyst	Firm, Analyst, Time
Observations	3077	2254	14954	12913
Adjusted R^2	0.291	0.416	0.370	0.435

Table 8: Effect of COVID-19 school closures on parents' forecast timeliness (continued)

Panel C: Triple difference analysis	(1)	(2)	(3)	(4)
School closure × Female Dummy × Having children	-0.110**	-0.138**	-0.149**	-0.133**
	(-2.08)	(-2.23)	(-2.47)	(-2.36)
School closure × Having children	0.023	0.025	0.021	0.022
	(1.27)	(1.32)	(1.06)	(1.24)
School closure × Female Dummy	-0.013	-0.000	-0.020	-0.003
	(-0.53)	(-0.01)	(-0.75)	(-0.14)
Female Dummy × Having children		0.064	0.000	0.000
		(1.18)	(0.00)	(0.00)
School closure	-0.041***	-0.087***	-0.043	-0.061**
	(-4.55)	(-3.05)	(-1.45)	(-2.05)
Having children		-0.007		
		(-0.41)		
Female Dummy		0.022		
		(0.82)		
Control variables	No	Yes	Yes	Yes
Fixed effects	Analyst	Firm, Broker, State, Time	Firm, Analyst, Time	Firm-quarter, Analyst, Time
Observations	18031	15341	15609	17935
Adjusted R^2	0.360	0.294	0.429	0.446

Table 9: Effect of COVID-19 school closures on the forecast release time

This table contains the regression results of *Housework-intensive time* on *Female*, *School closure* and their interaction term. *Housework-intensive time* is a dummy variable equal to one, if housework demand is usually high during the hour intervals (in the mornings, at lunch, or in the evening), and zero otherwise. All variables are defined in Appendix B. Standard errors are clustered by analyst and firm. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:		Housework-intensive time	
	(1)	(2)	(3)
Female × School closure	-0.090***	-0.096***	-0.099***
	(-3.32)	(-3.49)	(-3.57)
School closure	-0.054	0.014	0.007
	(-0.97)	(0.27)	(0.14)
Female	0.085***		
	(3.32)		
No. of firms followed			-0.000
			(-0.14)
Broker size			0.001
			(0.64)
Experience in the firm			-0.000*
			(-1.65)
Fixed effects	Firm, Broker, State, Time	Firm, Analyst, Time	Firm, Analyst, Time
Observations	17998	17858	17396
Adjusted R^2	0.113	0.196	0.195

Table 10: Effect of COVID-19 school closures on the forecast boldness and forecast accuracy

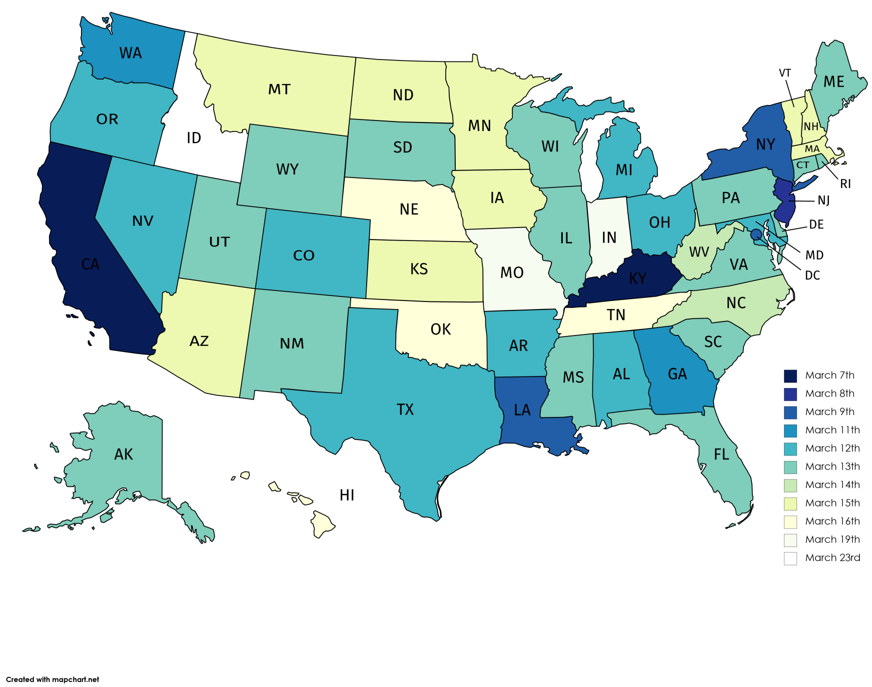
This table contains the regression results of forecast boldness measures on *Female*, *School closure* and their interaction term. *Distance from consensus* measures the deviation of the forecast from the consensus of analyst forecasts. *Distance from previous* measures the deviation of the forecast from the same analyst's previous forecast. *Accuracy improvement* is a dummy variable equal to one, if the forecast accuracy improves from the most recent forecast, and zero otherwise. *Forecast accuracy* measures the forecast accuracy of the forecast compared within all analysts forecasts issued in the same month for the same firm-quarter. Control variables include *No. of followed firms' EA*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm*. All variables are defined in Appendix B. Standard errors are clustered by analyst and firm. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Distance from consensus	Distance from previous	Accuracy Improvement	Forecast accuracy
	(1)	(2)	(3)	(4)
Female × School closure	0.064**	0.023	-0.027	-0.036
	(2.40)	(0.82)	(-0.90)	(-1.32)
School closure	0.016	0.021	0.002	0.101
	(0.27)	(0.26)	(0.02)	(1.45)
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Firm, Analyst, Time	Firm, Analyst, Time	Firm, Analyst, Time	Firm, Analyst, Time
Observations	15075	13664	15496	14254
Adjusted R^2	0.102	0.094	0.130	0.043

Appendix

A School closure start dates in each state in the U.S. during the COVID-19 Pandemic

This map contains the school closure dates manually collected based on the timestamps of the media coverage on school closure decisions across the states and official documents issued by the governors. The darker the color of the state is, the earlier school closures caused by the COVID-19 pandemic started.



B Variable description

This table describes all variables used in the empirical analyses. Data sources are as follows:

1. IBES: I/B/E/S database
2. Online: Manually collected online
3. CRSP: CRSP stock price data
4. Compustat: Compustat quarterly financial statement data
5. Facebook: Manually collected from analysts' Facebook pages
6. TR: Thomson Reuters Institutional (13f) Holdings
7. WVS: U.S. 2017 wave of the World Value Survey
8. Call: Earnings conference transcripts from Seeking Alpha
9. MC: Manually constructed

Variable name	Description	Data Source
Accuracy improvement$_{i,j,t}$	Dummy variable equal to one, if analyst i's forecast for firm i is more accurate compared with the previous analyst forecast for firm i of the same quarter.	IBES, MC
Bad earning news$_{i,t}$	Dummy variable equal to one, if firm i's realized earnings for quarter t are less than the analyst forecast consensus (the average of all available analyst earnings forecast values for the same firm-quarter) before quarter t's earnings announcement, and zero otherwise.	IBES, MC
Book to market$_{i,t}$	Firm i's book to market ratio at the fiscal end of quarter t	CRSP, Compustat
Broker size$_{j,t}$	The number of analysts working at the broker where analyst j works as of quarter t.	IBES, MC
Distance from consensus$_{i,j,t}$	The distance between the analyst forecast value and the consensus of analyst forecasts (the average of all available analyst earnings forecast values for the same firm-quarter). The measure is in relative term adjusted as in Equation 2.	IBES, MC
Distance from previous$_{i,j,t}$	The distance between the analyst j's forecast value and the previous forecast issued by analyst j. The measure is in relative term adjusted as in Equation 2.	IBES, MC
Female$_{j}$	Dummy variable equal to one, if the analyst is female, and zero otherwise.	IBES, Online, MC
Financial crisis$_{i,j,t}$	Dummy variable equal to one, if there is a financial crisis following the NBER definition when analyst j issues earnings forecast for firm i after its earnings announcement for quarter t, and zero otherwise.	MC
Firm size$_{i,t}$	Log of firm i's market value (in thousand dollars) at the fiscal end of quarter t.	CRSP, MC

Variable name	Description	Data Source
Forecast accuracy$_{i,j,t}$	Relative measure of the forecast accuracy calculated as in Equation 3.	IBES, MC
Forecast error$_{i,j,t}$	The absolute value of the difference between the analyst earnings forecast and the actual earning announced by the firm.	IBES, MC
Forecast revision$_{i,j,t}$	The difference between the analyst j's current forecast and his or her previous forecast on stock i.	IBES, MC
H1N1 school closure$_{i,j,t}$	Dummy variable equal to one, if schools in the state where analyst j is located are assumed to be closed when she issues earnings forecast for firm i after its earnings announcement of quarter t. The H1N1 school closures are captured by either comparing 2009 with the previous and subsequent years or comparing New York analysts with non-New York analysts in May and June 2009.	Online, MC
Having children$_{j,t}$	Dummy variable equal to one if analyst j's Facebook page contains photos of her non-adult children, and zero otherwise.	Facebook, MC
Housework-intensive time$_{i,j,t}$	Dummy variable equal to one, if analyst j releases the earnings forecast for firm i during the time period of a day when housework demand is high, i.e., in the morning from 7:00 to 9:00, at noon from 12:00 to 14:00, and from 17:00 to 21:00 in the evening, and zero otherwise.	IBES, MC
Institutional ownership$_{i,t}$	Firm i's institutional ownership in the percentage of total market value at the fiscal end of quarter t.	TR
Log number of following analysts$_{i,t}$	Log of the number of analysts who follow firm i as of the earnings announcement for quarter t.	IBES, MC
Liberal$_{j,t}$	Dummy variable equal to one, if the gender attitude index is larger or equal to the median in the sample, i.e., the gender attitude index of New York at 0.724, and zero otherwise.	WVS, MC
No. of firms followed$_{i,j,t}$	The number of firms for which analyst j issues an earnings forecast in quarter t.	IBES, MC
No. of industries followed$_{j,t}$	The number of industries analyst j covers in year t.	IBES, MC
No. of followed firms' EA$_{i,j,t}$	The number of followed firms' earnings announcements on the day when analyst j issues earnings forecast for firm i after its earnings announcement of quarter t.	IBES, MC
Participate$_{i,j,t}$	Dummy variable equal to one, if the analyst appears in conference call transcripts and the I/B/E/S database, and zero if analysts only appear in the I/B/E/S database.	IBES,Call, MC
Question count$_{i,j,t}$	The number of questions asked by analyst j at the firm i's conference call of quarter t.	Call, MC

Variable name	Description	Data Source
School closure$_{i,j,t}$	Dummy variable equal to one, if schools are closed in the state where analyst j is located at the time of firm i's earnings announcement for quarter t, and zero otherwise.	IBES, Online, MC
Sentence count$_{i,j,t}$	The number of sentences in the speech of analyst j at the firm i's conference call of quarter t.	Call, MC
Special items$_{i,t}$	Dummy variable equal to one, if the special items reported by firm i is positive in quarter t, and zero otherwise.	Compustat
Timely$_{i,j,t}$	Dummy variable equal to one, if analyst j issues the earnings forecast for quarter t+1 within one trading day (day 0 or day 1) after the firm i's quarter t earnings announcement date.	IBES, MC
Word count$_{i,j,t}$	The number of words in the speech of analyst j at the firm i's conference call of quarter t.	Call, MC

Internet Appendix

Locked-in at Home: Female Analysts' Attention at Work during the COVID-19 Pandemic

March 2021

I Facebook data collection process

This Internet Appendix section describes the details on how the analysts' Facebook pages are searched for and how the information on whether an analyst has children is collected.

To find an analyst's Facebook page, we follow the steps as follows:

1. Search for the analyst on LinkedIn or TipRanks based on the analysts' full name, company name, and the city where she works in to get a photo of the analyst;

2. If her photo is not available on the above two websites, google the analyst's the analysts' full name and company name for a photo of the person (e.g., a photo at an interview on TV);

3. Search for the analyst's full name on Facebook and compare photos of the analysts with the same name against the profile photos on LinkedIn or TipRanks or photos from Step 2;

4. If there is no match of photos, google "Facebook"+"analyst full name"+"analyst location" and check whether there is a matched Facebook page;

5. If there is no match, google "Facebook"+"analyst full name"+"the company the analyst currently works in (from LinkedIn)" and check whether there is a matched Facebook page

6. If there is no match, google "Facebook"+"analyst full name"+"the universities the analyst attended (from LinkedIn)" and check whether there is a matched Facebook page;

7. If there is still no match, assume there is no public Facebook page of the analyst;

8. To ensure the accuracy of photo matching, two individuals independently collect analysts' Facebook pages following the above steps. If there is any inconsistency, i.e., one person finds the link while the other does not (around 10% of links collected in the first round) or different Facebook links are collected (only less than 1% of links collected in the first round), a third person makes the judgement on whether the Facebook page (or which Facebook page) should be used.

After getting an analyst's Facebook page, we check the posted photos to identify whether she has children. The children in the photo may not be the person's children but e.g., her nephews or nieces. The identity of the children is distinguished based on the texts and comments in the posts.

If the analyst has children, we also estimate the children's ages. If the analyst has posted photos of the children's birth or birthday celebrations, it is possible to accurately identify the children's age. Otherwise, we estimate whether a child's age is among the following age groups: younger than 3, 3 to 5, 5 to 10, 10 to 15, 15 to 18, or older than 18, based on the photos of the children and the time when these photos were posted.

As shown in the table below, we finally find Facebook pages for 682 analysts, 262 out of which have non-adult children.

	No Facebook	Facebook found	% Facebook found	Have children	% Children	Non-adult children	% Non-adult children
Male	1,089	590	35.14%	255	43.22%	228	38.64%
Female	109	92	45.77%	35	38.04%	34	36.96%
Total	1,198	682	36.28%	290	42.52%	262	38.42%

Previous studies show that in the general population, women are more likely to use Facebook (Acquisti and Gross (2006)) and share personal topics such as families (Wang et al. (2013)). Among financial analysts, women are also more likely to have Facebook pages than men (45.77% vs 35.14%). However, women are not more likely to post photos their children (38.04% vs 43.22%). It is also possible that female analysts are less likely to have children, compared with male analysts because this is a very competitive profession, and having a children is more costly for women.

II Analysts' activities at earnings conference calls

In this Internet Appendix section, I present the detailed analyses and results on analysts' activities at earnings conference calls.

I construct a sample consisting of conference call transcripts for earnings conference calls from January 2020 to August 2020. The conference call transcripts are obtained from Seeking Alpha. I extract the analysts' names from the transcripts and match them with the analysts that issue forecasts for the firm in the quarter based on the I/B/E/S database. The sample uses 7,064 conference transcripts and contains 29,369 observations on firm-analyst-call date level with 3174 distinct firms, 1701 analysts of which 186 are female. Panel A in Table IA4 contains the summary statistics of variables in the sample. Similar to the main sample, 10% of analysts who participate in the conference calls are female. On average, an analyst who participates in a conference call asks 2.68 questions, using 163.35 words and 12.58 sentences.

Table IA5 contains the regression results of the question length or the question number in earnings conference calls on *Female*, *School closure* and their interaction terms. All regressions control for No. of followed firms' EA to measure the distraction of concurrent earnings announcements (Driskill et al. (2020)), Forecast revision from consensus (Mayew (2008)), and firm and analyst characteristics. The COVID-19 school closures have negative effects on the question length and the question number of female analysts at the earnings conference calls while the effect on those of male analysts is not significant. Female analysts use 9 fewer words (5.5% of the sample average in Table IA4), 0.648 fewer sentences (5.15% of the sample average in Table IA4), and ask 0.150 fewer questions (5.6% of the sample average in Table IA4) at earning conference calls after the COVID-19 school closures. The effect is statistically significant at the 1% level in models controlling for firm, broker, state, and time fixed effects (Column (1), Column (3), and Column (5)) and is still statistically significant at the at least 10% after controlling for analyst fixed effects (Column (2), Column (4), and Column (6)).

Furthermore, taking one step back and considering the probability to participate in earnings conference calls, I expect female analysts are less likely to ask questions after the school closure. In a similar vein, Driskill et al. (2020) finds that analysts distracted by multiple concurrent earnings announcements in their coverage portfolio are less likely to ask questions at earnings conference calls. In order to determine the probability of participating in an earnings conference call, I make assumptions on the analysts that potentially participate in the earnings conference call. Following Mayew (2008), I define a pool of analysts that potentially ask questions at conference calls as analysts that issue a forecast for firm in the quarter in the I/B/E/S database. Participate is a dummy variable equal to one if analysts appears in conference call transcripts and the I/B/E/S database, and zero if analysts only appear in the I/B/E/S database. As shown in Panel B of Table IA4, 46% of analysts who follow a firm in the quarter participate in the firm's earnings conference call, asking questions and therefore, appearing in the respective conference transcript.

At the aggregated level in the whole sample, I do not find a significant effect of the COVID-19 school closures on the participation of conference calls. I conjecture that the effect may vary for conference calls happening at a different time of day. I extract the time of the conference call from conference transcripts and transfer the time to the local time of the state where the analyst is located. I obtain the time of the conference calls for 76% of the sample. Based on the local time, I define a dummy variable for each hour interval. Then I run regressions of *Participate* on a dummy variable indicating whether the earnings conference call is held during the hour of the day, the female dummy, the school closure dummy, and their interaction terms, controlling for analyst and time (earnings conference call date) fixed effects and clustering the standard errors by analyst. Figure IA3 plots the coefficient estimates of the interaction terms between the hour interval, *Female*, and *School closure* for each hour intervals. It seems that the COVID-19 school closures have a larger negative effect on the probability for a female analyst to participate in earnings conference calls during most time of the day. However, the effect is only statically significant at the 10% level for conferences held in the morning from 5:00 to 6:00 or at noon from 11:00 to 12:00.

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Figure IA1: Timeliness of male and female analysts' earnings forecasts from 1999 to 2020

This figure plots the average of the dummy variable Timely among male analysts and female analysts over the years from 1999 to 2020.

Figure IA2: Gender equality index for each state from the World Value Survey

This map contains the gender attitude index for each state from the U.S. 2017 wave of the World Value Survey. The survey asks about respondents' gender attitudes on women regarding jobs, political positions, and education. The gender attitude index for each state is calculated by taking the average of these three measures among respondents from the state. The darker the color of the state is, the more conservative gender attitudes in the state are.

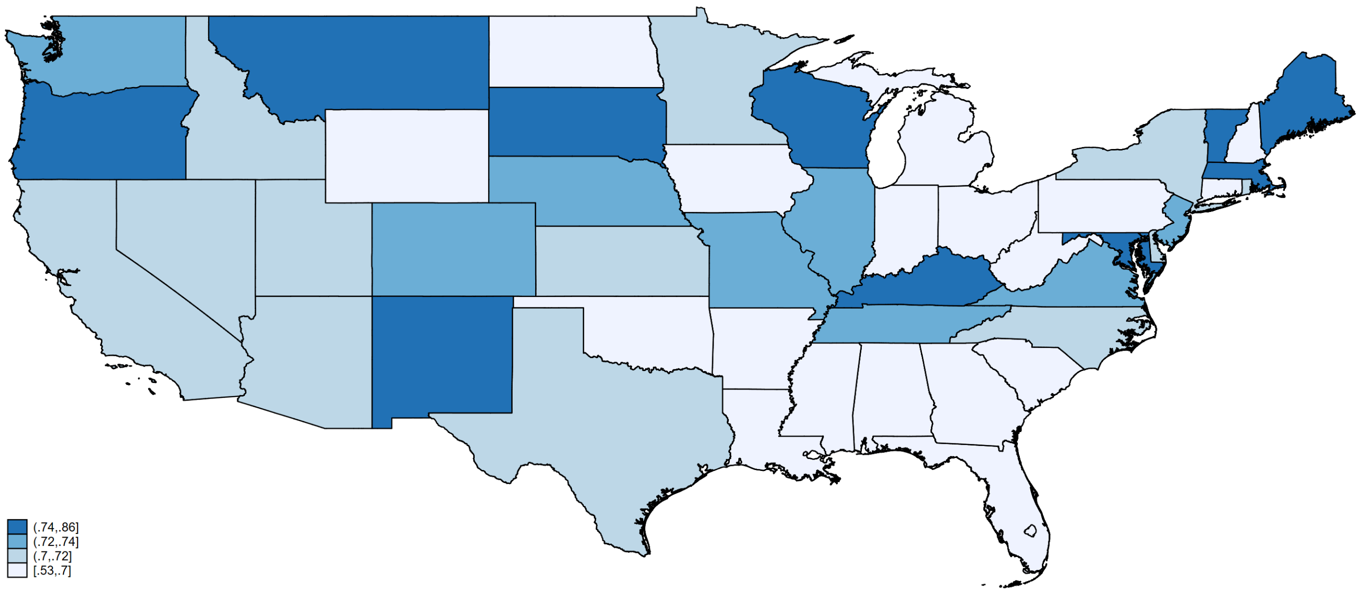

Figure IA3: Effect of school closures on forecast issue time among male and female analysts

This figure plots the coefficient estimates of the triple-interaction terms in the regressions of *Participate* on a dummy variable indicating whether the earnings conference call is held during the hour of the day, the dummy variable *Female*, the dummy variable *School closure*, and their interaction terms. The regressions control for analyst and time (earnings conference call date) fixed effects, and the standard errors are clustered by analyst. The confidence intervals of the coefficient estimates are at the 90% level.

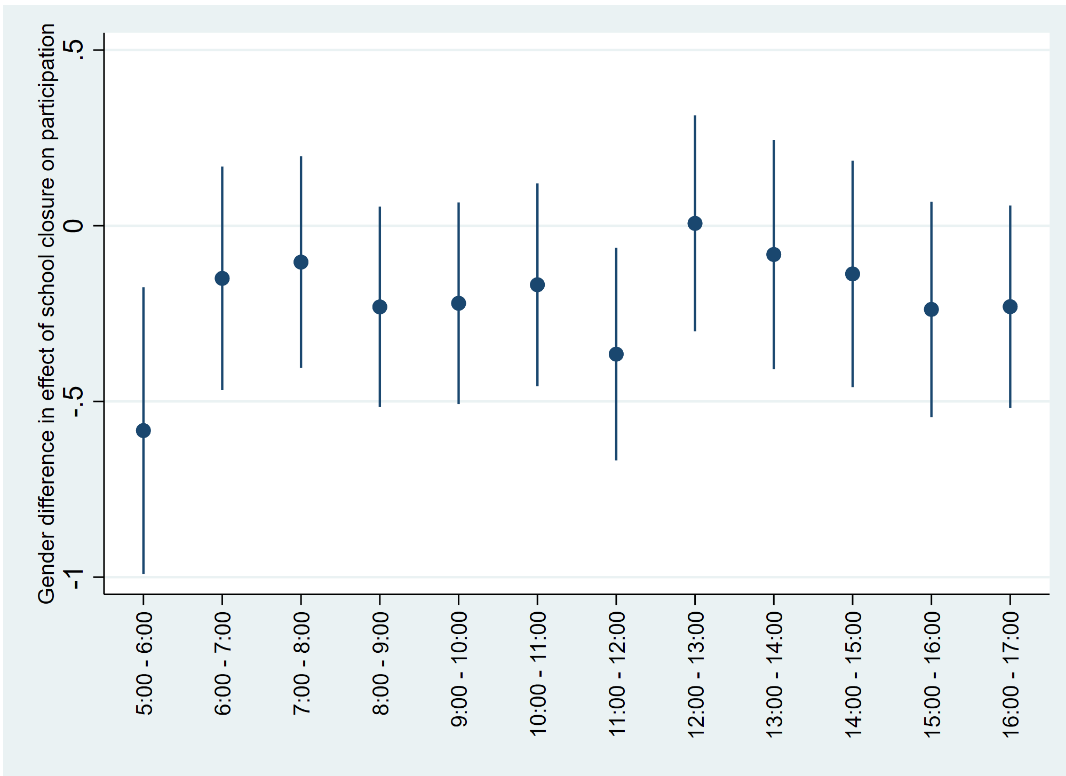

Table IA1: Robustness check in the sample not excluding earnings announcements before school closures with analysts' forecasts after school closures

This table contains the regression results of *Timely* on *Female*, *Financial crisis* and their interaction term in the sample of earnings announcements from January 2020 to August 2020. Earnings announcements are not excluded from the sample if earnings announcements happened before school closures in a state, and a forecast of an analyst in that state was issued after school closures. *Timely* is a dummy variable equal to one, if the analyst issues an earnings forecast for quarter t+1 within one trading day (day 0 or day 1) after the firm's quarter t earnings announcement date, and zero otherwise. Control variables include *No. of followed firms' EA*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm*. All variables are defined in Appendix B. Standard errors are clustered by analyst and firm. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Timely			
	(1)	(2)	(3)	(4)
Female × School closure	-0.070***	-0.053***	-0.059***	-0.054***
	(-3.07)	(-2.61)	(-2.95)	(-2.71)
School closure	-0.221***	-0.179***	-0.653***	-0.593***
	(-18.87)	(-17.29)	(-41.14)	(-34.78)
Female	0.064***		0.062***	
	(3.46)		(3.57)	
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Firm, Broker, State	Firm, Analyst	Firm, Broker, State, Time	Firm, Analyst, Time
Observations	24858	25370	24858	25370
Adjusted R^2	0.312	0.435	0.392	0.499

Table IA2: Continuous measure of forecast timeliness

This table contains the regression results of the continuous measure of forecast timeliness on *Female*, *School closure* and their interaction term. The continuous measure of forecast timeliness is the Log form of the number of days between earnings announcements and analyst forecasts. Control variables include *No. of followed firms' EA*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm.* All variables are defined in Appendix B. Standard errors are clustered by analyst and firm. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:		Timely	
	(1)	(2)	(3)
Female × School closure	0.067	0.089*	0.081*
	(1.28)	(1.82)	(1.65)
School closure	0.129**	0.096	0.109*
	(2.49)	(1.53)	(1.71)
Female	-0.076**		
	(-1.99)		
Control variables	Yes	Yes	Yes
Fixed effects	Firm, Broker, State, Time	Firm, Analyst, Time	Firm-quarter, Analyst, Time
Observations	15208	15378	15347
Adjusted R^2	0.292	0.428	0.429

Table IA3: Correlations

This table shows pairwise correlation coefficients between all variables used in the analysis. A detailed description of all variables is provided in Appendix B. ∗ ∗ ∗, ∗∗, and ∗ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) Female Dummy	1.000																
(2) School close	0.010	1.000															
(3) Timely	0.026***	-0.119***	1.000														
(4) Distance from consensus	0.013*	0.003	0.054***	1.000													
(5) Distance from previous	0.011	0.022***	-0.022***	0.482***	1.000												
(6) Accuracy improvement	-0.011	-0.004	0.031***	-0.109***	-0.071***	1.000											
(7) Forecast accuracy	-0.024***	0.039***	-0.001	-0.197***	-0.100***	0.493***	1.000										
(8) No. of followed firms' EA	0.011	-0.004	-0.080***	-0.013*	0.016**	0.007	-0.018**	1.000									
(9) No. of firms followed	-0.020***	0.019**	0.064***	0.012	0.010	-0.010	-0.014*	0.324***	1.000								
(10) Broker size	0.065***	0.044***	0.062***	0.027***	-0.003	0.016**	-0.002	0.017**	0.146***	1.000							
(11) Experience in the firm	-0.018**	0.050***	0.030***	-0.007	0.004	0.020***	0.017**	0.068***	0.082***	0.045***	1.000						
(12) Firm size	0.006	-0.037***	0.081***	-0.001	-0.003	0.028***	0.038***	-0.021***	-0.034***	0.104***	0.145***	1.000					
(13) Institutional ownership	0.001	0.184***	-0.076***	-0.016**	-0.012	-0.015*	-0.013*	-0.021***	0.006	-0.011	-0.022***	-0.769***	1.000				
(14) Book to market	0.008	0.051***	-0.127***	-0.014*	0.002	0.012	0.010	0.140***	0.069***	-0.004	0.031***	-0.107***	0.115***	1.000			
(15) Bad earning news	0.012*	0.024***	-0.054***	0.013*	0.009	0.010	0.009	0.061***	0.015**	-0.045***	-0.036***	-0.052***	0.024***	0.080***	1.000		
(16) Special items	-0.040***	-0.044***	-0.003	-0.004	-0.007	-0.005	-0.005	-0.076***	-0.029***	0.036***	0.060***	-0.024***	0.031***	-0.060***	-0.115***	1.000	
(17) Log number of following analysts	-0.002	0.121***	0.081***	-0.043***	-0.024***	0.029***	0.052***	-0.057***	0.004	0.146***	0.178***	0.398***	-0.043***	-0.091***	-0.098***	0.040***	1.000

Table IA4: Summary statistics for the sample of earnings conference calls

This table contains summary statistics, including the number of observations (Obs), mean, standard deviation (Std. Dev.), 25% percentile (P25), median, and 75% percentile (P75), for the earnings conference calls from January 2020 to August 2020. Panel A contains summary statistics for the sample of I/B/E/S analysts participating in the earnings conference calls and Panel B contains summary statistics for the sample of I/B/E/S analysts following the firms in the quarter of the earnings conference call, i.e., analysts participating or potentially participating the conference call. All variables are defined in Appendix B.

Variable	Obs	Mean	Std. Dev.	P25	Median	P75
Panel A: Analysts participating the conference call						
Word count	29369	163.35	98.06	100.00	146.00	203.00
Sentence count	29369	12.58	7.38	8.00	11.00	16.00
Question count	29369	2.68	1.74	2.00	2.00	3.00
Female Dummy	29369	0.10	0.30	0.00	0.00	0.00
School closure	29369	0.52	0.50	0.00	1.00	1.00
No. of followed firms' EA	29314	0.91	1.38	0.00	0.00	1.00
Forecast revision from consensus	28044	-0.04	0.29	-0.08	-0.01	0.03
No. of firms followed	29238	17.50	7.64	13.00	17.00	22.00
Broker size	29360	48.78	32.53	21.00	49.00	68.00
Experience in the firm	29255	22.24	22.24	6.00	15.00	32.00
Firm size	29223	15.18	1.89	13.98	15.20	16.41
Institutional ownership	29205	0.09	0.09	0.05	0.06	0.10
Book to market	28871	0.61	0.87	0.15	0.33	0.69
Bad earning news	29077	0.34	0.48	0.00	0.00	1.00
Special items	28866	0.66	0.47	0.00	1.00	1.00
Log number of following analysts	29099	2.48	0.59	2.08	2.56	2.89
Panel B: Analysts participating or potentially participating the conference call						
Participate	63396	0.46	0.50	0.00	0.00	1.00
Female Dummy	63396	0.10	0.30	0.00	0.00	0.00
School closure	63396	0.54	0.50	0.00	1.00	1.00

Table IA5: Effect of COVID-19 school closures on analysts' activities at the earnings conference calls

This table contains the regression results of question length or question numbers in earnings conference calls on *Female*, *School closure* and their interaction terms in the sample of I/B/E/S analysts participating in the earnings conference calls from January 2020 to August 2020. Control variables include *No. of followed firms' EA*, *Forecast revision from consensus*, *Firm size*, *Institutional ownership*, *Book to market*, *Bad earning news*, *Special items*, *Log number of following analysts*, *No. of firms followed*, *Broker size*, and *Experience in the firm*. All variables are defined in Appendix B. Standard errors are clustered by analyst and firm. t-statistics are provided in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Word count		Sentence count		Question count	
Female Dummy × School closure	-9.154***	-6.614**	-0.648***	-0.410*	-0.150***	-0.105**
	(-2.92)	(-2.27)	(-2.66)	(-1.84)	(-2.79)	(-2.13)
School closure	8.822	-1.429	0.168	-0.224	0.114	0.036
	(0.88)	(-0.16)	(0.20)	(-0.30)	(0.56)	(0.20)
Female Dummy	-5.928		-0.261		0.049	
	(-1.38)		(-0.88)		(0.69)	
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Firm, Broker, State, Time	Firm, Analyst, Time	Firm, Broker, State, Time	Firm, Analyst, Time	Firm, Broker, State, Time	Firm, Analyst, Time
Observations	27275	27183	27275	27183	27275	27183
Adjusted R^2	0.390	0.581	0.421	0.562	0.481	0.580