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Locked-in at home: The gender difference in analyst forecasts after the COVID-19 school closures

Mengqiao Du

National University of Singapore, NUS Business School, 15 Kent Ridge Drive, 119245, Singapore

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ABSTRACT

This paper explores the shock of school closures caused by the COVID-19 pandemic to study the effect of childcare responsibilities on analyst forecasts. With manually collected data on whether analysts have children, I find that female analysts with children (mother analysts) are less likely to issue timely forecasts after school closures, compared to male analysts with children (father analysts). Mother analysts' forecasts also become less accurate after school closures, but the negative effect only exists among forecasts for firms with relatively low institutional ownership, suggesting that mother analysts prioritize maintaining the forecast accuracy for firms that are more important to their careers. Additionally, mother analysts shift forecast release times to avoid childcare hours. My findings imply that childcare responsibilities hurt the productivity of mother analysts more than that of father analysts, even though these women have established themselves in a competitive industry.

1. Introduction

This paper examines whether the COVID-19 school closures are more likely to influence the forecasts of female analysts with children (mother analysts) than those of male analysts with children (father analysts). There is survey evidence in the previous literature that women spend more time on parenting and other domestic tasks than men (e.g., Baxter (1997); Hewlett (2002)). The model in Becker (1985) shows that it is optimal for men and women within households to specialize their labor provision. Women are usually the ones who spend more time on energy-consuming housework, such as childcare, so they have less time and energy per unit of time for market work. Therefore, I expect the exogenous increase in childcare responsibilities after COVID-19 school closures to be more associated with the productivity of mother analysts rather than that of father analysts.

The large-scale and unexpected school closures increased childcare demand at home in households with school-age children (e.g., Power (2020)).[1] After the pandemic started, each U.S. state decided on school closures, and the school closures can thus be plausibly viewed as exogenous to people's labor market decisions. In addition, the school closure dates

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E-mail address: m.du@nus.edu.sg.

[1] 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. based on statistics from Map: Coronavirus and School Closures (2020, March 6), Education Week, Retrieved May 2020 at https://www.edweek.org/ew/section/multimedia/map-coronavirus-and-school-closures.html.

differed across states. These staggered school closures provide a quasi-natural experiment to study the effect of childcare responsibilities on work productivity.

It is, in general, impossible to observe and measure work productivity, especially for professions not applicable to a piece rate system. Therefore, it is empirically difficult to study the effect of childcare responsibilities on the productivity of high-achieving women. The profession of sell-side equity analysts presents a unique context to study the effect of the COVID-19 school closures on the labor market productivity because analysts' work productivity is quantifiable and comparable based on their forecasts. Analysts' productivity can be measured by the timeliness and accuracy of their forecasts. These measures are widely used in the literature and have important implications for firms' information environments and analysts' careers (Bradshaw (2011); Bradshaw et al. (2017); Brown et al. (2015)). In addition, corporate earnings announcements and analysts' forecast releases have detailed timestamps in the data, enabling the observation of changes in analysts' productivity in the short window around the COVID-19 school closures.

It is ex-ante unclear whether female analysts' work productivity is more likely to be negatively associated with childcare responsibilities than that of male analysts. On the one hand, female analysts may not assume more childcare responsibilities than male analysts because they have self-selected into this competitive and lucrative industry and have similar backgrounds to male analysts (Kumar (2010); Fang and Huang (2017)). Female analysts thus may not resemble women in other professions regarding time and effort spent on childcare. On the other hand, the productivity of female analysts may be more harmed by childcare responsibilities than that of male analysts, even though they have managed to succeed in their careers. A nationwide survey by Hewlett (2002) shows that high-achieving women spend more time and effort on childcare responsibilities than do comparable men. Therefore, empirically comparing the forecasts of female analysts with those of male analysts when childcare responsibilities increase around the COVID-19 school closures can help illuminate how the productivity of professional mothers in competitive industries is associated with childcare responsibilities.

With manually collected data on whether analysts have children, this paper examines earnings forecasts of analysts with children in the I/B/E/S database around the COVID-19 school closures. I exploit exogenous variation in the timing of the school closure decisions across states and conduct a difference-in-differences estimation. This approach allows for a comparison of changes in forecast characteristics of mother and father analysts after school closures.

To begin, I study the effect of childcare responsibilities on forecast timeliness because analysts are likely to delay their work after the COVID-19 school closures when they have more childcare responsibilities. After the school closures, mother analysts are 13.6 percentage points (pp) less likely to issue timely forecasts after earnings announcements, compared to father analysts, when firm and analyst fixed effects and time-varying firm and analyst characteristics, such as firm size and brokerage size, are controlled for. The difference is economically significant, given that it accounts for 17.4% of the average forecast timeliness in the sample. The effect is statistically significant at the 1% level in all model specifications, even after including analyst and firm × quarter fixed effects. In addition, I divide the sample based on the analysts' youngest children's ages to examine the heterogeneous effects of school closures on analysts with children at different ages. The effect of the COVID-19 school closures on forecast timeliness is expected to be among female analysts with school-age children because they are directly influenced by school closures. The children's ages are estimated based on Facebook posts and photos and can be divided into three groups: pre-primary (under six years old), school-age (between six and 18), and adulthood (older than 18 years old).[2] The results show that the forecast timeliness of female analysts with children from six to 18 years old decreases by 19 pp after school closures. The decrease is larger than the decrease in forecast timeliness among female analysts with children younger than six (19 pp versus 9 pp), possibly because the treatment of the COVID-19 school closures captures the increase in childcare responsibilities for mothers with school-age children. By contrast, among female analysts with children older than 18 years old, the effect of school closures on forecast timeliness is statistically insignificant.

In the next step, I use the same difference-in-differences estimation to examine the association between school closures and forecast accuracy. Mother analysts' accuracy may decrease after school closures, as their childcare responsibilities increase. However, analysts may be able to maintain forecast accuracy by delaying their forecasts (Cooper et al. (2001); Clement and Tse (2003)) or strategically allocating effort to a subset of firms in their coverage portfolios (Harford et al. (2019); Chiu et al. (2021)) as forecast accuracy is the critical trait of forecast performance impacting on analysts' careers (e.g., Mikhail et al. (1999), Bradshaw et al. (2017), and Brown et al. (2015)). The results show that the gender difference in the effect of school closures on forecast accuracy is statistically insignificant in most model specifications. On average, mother analysts do not issue less accurate forecasts compared to father analysts after school closures.

I further investigate the heterogeneous effects of school closures on different firms in mother analysts' coverage portfolios. The literature finds that analysts strategically allocate effort to firms that are more important to their careers, namely, those with high institutional ownership (Harford et al. (2019); Chiu et al. (2021)). I split the sample based on the relative institutional ownership of a firm within an analyst's portfolio and conjecture that, after the school closures, mother analysts issue less accurate forecasts only for firms with relatively low institutional ownership because firms with higher institutional ownership deliver more lucrative commission revenue for the brokerage (Frankel et al. (2006)). Moreover, analysts depend on institutional investors for performance ratings (Ljungqvist et al. (2007)), for example, "All-Star" analyst nomination. The results show that mother analysts' forecasts for firms with relatively high institutional ownership do not become less accurate

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[2] Three research assistants independently estimate the children's age groups. See Section 2.1 and Internet Appendix I for data collection and validation details.

after school closures. By contrast, for firms with relatively low institutional ownership, the forecast accuracy of mother analysts decreases by 9.6 pp after school closures, compared to that of father analysts, which corresponds to 17.1% of the average forecast accuracy in the sample.

Mother analysts may also adjust the time of day when they work after the COVID-19 school closures. Given the nature of the work, analysts have some autonomy on when they issue their forecasts and may choose to work when they are less likely to be occupied with childcare. Analysts may need to take care of the children and cook meals for them during the daytime and therefore, will have to issue their forecasts at night when their children go to sleep. I approximate analysts' working time with the time of day they release their forecasts. I find that mother analysts are 27% less likely to release forecasts during hours when they are likely to provide childcare after school closures. By contrast, father analysts' forecast release time does not change significantly. These results suggest that mother analysts have to adjust their work schedule in response to childcare responsibilities.

The sample in previous analyses may exclude some analysts who have children but cannot be found on either Facebook or thatsthem.com.[3] In the next step, I extend the analyses to the sample of all analysts, regardless of whether they can be identified as having children based on my approach, to provide additional evidence on the gender difference in the effect of school closures on analyst forecasts. A smaller school closure effect is expected in the sample of all analysts (including those who do not have children or have adult children). Consistent with expectations, I find that female analysts are less likely to issue timely forecasts, compared to male analysts, but the economic magnitude is smaller than that in the sample of analysts who are identified as having children (6.7 pp versus 13.6 pp).

An alternative explanation for the baseline findings is that female analysts are more risk-averse (e.g., Powell and Ansic (1997)) and less overconfident (e.g., Lenney (1977); Barber and Odean (2001)) than male analysts, so they delay their forecasts more than male analysts after the outbreak of the COVID-19 pandemic. In that case, female analysts without children would delay their forecasts more than male analysts without children after the COVID-19 school closures as well. In the sample of all analysts, I run a regression of the forecast timeliness on the triple interaction term among *School closure*, *Female*, and *Having children*. The finding confirms that the forecasts of mother analysts, rather than female analysts who are not identified as having children, become less timely after school closures, compared to those of their male counterparts, which helps rule out the potential alternative explanation of gender traits.

I further explore the shock of school closures during the 2009 H1N1 pandemic to test the validity of the baseline findings after other school closures. I find a significant reduction in female analysts' forecast timeliness after school closures in 2009 as well. In addition, the time of the COVID-19 school closures overlaps with a financial crash. Female analysts may tend to delay their forecast releases more than male analysts after this crash because they are more risk-averse or less overconfident (e.g., Powell and Ansic (1997); Lenney (1977); Barber and Odean (2001)). To empirically investigate this potential alternative explanation, I test whether there is any gender difference in analysts' forecast timeliness during the 2001 or 2008 financial crises. I find no strong gender difference in forecast timeliness after these financial crises. Therefore, the baseline findings are not likely to be driven by the financial crash in March 2020. Finally, I conduct various robustness tests and confirm that the results are robust to using different sample periods and measures of forecast timeliness.

The paper contributes to several strands of literature. First, it identifies a new factor that affects analysts' productivity, namely, childcare responsibilities, with an exogenous shock. Given that childcare demand in the household is likely to increase after COVID-19 school closures, and the staggered COVID-19 school closures are arguably exogenous to the work productivity of analysts, the findings help establish a causal relation between childcare responsibilities and the work productivity of mother analysts. These findings contribute to the literature showing that analysts are less productive 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)). Analysts also 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)).[4] Consistent with these findings, I show that mother analysts manage to maintain forecast accuracy for firms with high institutional ownership after school closures.

My findings also add to the understanding of the social effects of COVID-19. Many recent papers focus on the effect of COVID-19 on financial markets (e.g., Ding et al. (2020); Baker et al. (2020)) and social inequality (e.g., Alon et al. (2020); Brown and Ravallion (2020); Collins et al. (2021)). Differing from other papers that document an unequal impact of COVID-19 on men and women (e.g., Barber et al. (2020) and Cui et al. (2021)), this paper focuses on financial analysts, whose productivity can be directly measured based on their forecasts. It is noteworthy that female analysts' forecasts are more likely to be influenced by school closures than those of male analysts, even though these female analysts have established themselves in a competitive industry.

Finally, the paper contributes to the broader literature on gender issues in the financial industry and top positions in firms (e.g., Kumar (2010), Huang and DarrenKisgen (2013), Fang and Huang (2017); Niessen-Ruenzi and Ruenzi (2019)) and in labor

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[3] Specifically, my methodology of identifying whether analysts have children can result in false negatives; that is, I may identify some analysts as not having children, even though they do.

[4] Timely forecasts play an important role in improving market efficiency, in the sense that they facilitate price discovery (Zhang (2008)). In addition, 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.

markets in general (e.g., Niederle and Vesterlund (2007), Goldin (2014)). It provides empirical evidence for the Becker (1985) theory in the setting of sell-side equity analysts. Furthermore, the finding in the paper implies how successful professional women try to mitigate the harm of school closures on their careers: they manage to maintain the accuracy level of forecasts that are more important to their careers.

2. Sample construction and variable definitions

2.1. Data and sample

2.1.1. Analyst forecasts and identity

Earnings announcements and individual analysts' earnings forecasts are obtained from the I/B/E/S database. The sample contains earnings announcements from January to June 2020 to cover a roughly symmetric window around the COVID-19 school closures.[5] To capture analysts' reaction to earnings announcements (Driskill et al. (2020); Zhang (2008)), the sample includes 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 data to obtain stock price and accounting information of the firm as of quarter t.

Following the literature (e.g., DeHaan et al. (2015)), I drop stocks with a price below $1 as of the fiscal end of quarter t to avoid the influence of penny stocks. In addition, firms with only one following analyst in the quarter are excluded from the sample because I compare forecasts provided by different analysts for a particular firm in a certain quarter (Clement and Tse (2005) and Driskill et al. (2020)). I also require that the forecast in the sample is not the first or the last of an analyst for a firm (Zhang (2008); Driskill et al. (2020)) because these analysts may have different incentives (e.g., Irvine (2004)) and hence different responsiveness to earnings announcements, compared to analysts with continual coverage.

I/B/E/S only provides analysts' last names and first initials. To identify the gender of the analysts, I manually collect the full name and identify the gender based on Linkedin profiles, official websites of the brokerages, and media coverage. If I cannot identify the gender from the information online, including photos and the third-person pronouns "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.[6] I can determine the gender of analysts for 97.7% of the sample and the location for 91.7% of the sample.

2.1.2. Childcare responsibilities

Child-rearing duties are critical for the analyses in this paper. Therefore, in the main analyses, I restrict the sample to analysts identified as having children in main analyses. I collect data on parent status by checking Facebook pages. I identify Facebook pages for 680 analysts.[7] Based on the information from Facebook posts, 280 analysts are identified as having children. To avoid self-selection of whether to have a public Facebook page, I supplement the family condition data collected from Facebook pages by searching for the analysts' names and their locations on thatsthem.com, which is a free people search engine that provides people's addresses, emails, phones, and various other information including the number of children they have. I find 557 financial analysts on the website, and 283 have more than one child based on the number of children provided by the website. The details of the data collection process are described in Internet Appendix I.

Children's ages are expected to be related to the treatment effect of school closures. Analysts with adult children should be excluded from the main sample as they are unlikely to be influenced by the increase in childcare after school closures.[8] I use Facebook posts and photos to estimate children's ages. There are 266 analysts who have posted enough information to estimate the ranges of their children's ages on Facebook. Three research assistants are asked to group the ages of the youngest children into one of the following groups: younger than three, three to five, six to 10, 11 to 15, 16 to 18, or older than 18. If the analyst has posted photos of the children's birth or birthday celebrations, the children's age can be relatively accurately identified. In cases where the research assistants must estimate children's ages based on the photos, they choose the same group of ages for most analysts (257 out of 266 analysts). If I accumulate the age groups to three, namely, younger than six, six to 18, and older than 18, there is no conflicted judgment made by these three research assistants. The classification of three age groups is sufficient for the analyses of this paper.

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[5] The sample covers forecasts for the first and second quarters of 2020. Before- and after-school-closure forecasts contain forecasts for both quarters, even though more than 90% of before(after)-school-closure forecasts are for the first (second) quarter in 2020. The timing of forecasts does not influence the analysis as long as there is no gender difference in analysts' forecasts for these two quarters. To further rule out the potential bias caused by the calendar timing of forecasts in the window around school closures, robustness checks in Section 5.3 confirm that the results are robust to using a sample of forecasts with the same calendar time in a year, i.e., forecasts after school closures in 2020 and in respective time periods in 2019, or a sample of forecasts in the shorter window of March 2020.

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

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

[8] There are 30 analysts whose children are adults based on Facebook posts. I exclude these analysts from the main sample to avoid imprecise classifications of the treatment and control groups. The results are robust to including these analysts in either the treatment or the control group.

It is not possible to estimate the children's ages for 24 analysts even though their Facebook posts indicate that they have children. In addition, for analysts who can only be identified as having children on thatsthem.com instead of Facebook pages, their children's ages are also unknown as the information on children's ages is not available on thatsthem.com. In the main sample, these analysts are assumed as having children under 18. Potentially having analysts with children older than 18 in the treatment group may underestimate the school closure effects.[9]

The sample of analysts with children may exclude some analysts who have children but cannot be found on either Facebook or thatsthem.com or do not post photos of their children on Facebook pages. Nevertheless, using this restrictive sample ensures that I focus on analysts who face an increase in childcare responsibilities after the COVID-19 school closures.

2.1.3. School closures

Data on school closures 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 and second, many schools started to shorten the teaching day or closed after the state announcement but before the required latest closure dates. The map in Appendix A contains manually collected school closure dates, which range from March 7 to March 23. The darker the color of the state, the earlier school closures started. California and Kentucky were among the first states to announce school closure decisions.

For a firm's earnings announcement after (before) school closures, the subsequent forecasts for the firm's next-quarter earnings are considered as the treatment (control) group. However, one type of earnings announcement before school closures needs to be dropped from the sample to define an unbiased treatment effect of school closures on financial analysts. These cases are demonstrated in Fig. 1. Firm A announced earnings before the school closures, and Analyst X issued a forecast for Firm A after the school closures. Analyst X's forecast should not be considered as part of the control group, as it was issued after school closures. It would also be problematic to classify Analyst X's forecast into the treatment group because doing so would lead to a systematic upward bias in estimating the treatment effect of school closures: Analyst X's forecast (the treatment group) would be systematically less timely than any analyst forecasts for Firm A before school closures (the control group), for example, Analyst Y's forecast as demonstrated in the figure.[10,11]

Therefore, to have a rigorous identification of the treatment effect of school closures, I exclude this type of earnings announcements, that is, the cases in which a firm announced earnings before school closures, and an analyst issued forecasts for this firm after school closures. I thus exclude 11,247 observations from the sample.

The sample of all analysts includes 18,750 firm-quarter-analyst observations, with 2201 firms and 1880 analysts, of which 201 are female analysts. The sample of analysts who are identified as having children based on the information from Facebook and thatsthem.com (the main sample) contains 5938 observations with 453 distinct male analysts and 54 distinct female analysts. To be included in the sample, *Timely* and all control variables should have non-missing values, which reduces the sample size to 15,208 in the sample of all analysts and 4726 in the main sample, respectively.

Another issue regarding the definition of the school-closure treatment effect is whether these state-level school closure policies involved private schools. This question is relevant because financial analysts earn a relatively high income and are likely to send their children to private schools. However, assuming school closure mandates applied to both public and private schools when the mandate might only apply to public schools works against finding any results. In addition, many private
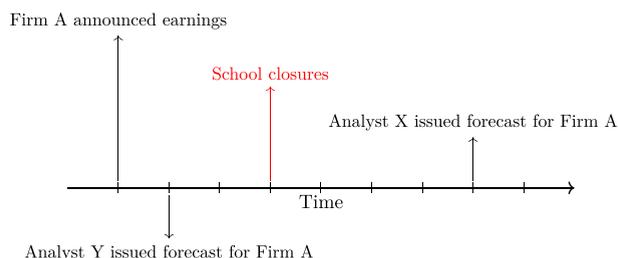

Fig. 1. An example of observations excluded to define the school closure treatment. This figure contains an example demonstrating the cases where a firm announced earnings announcements before school closures, and an analyst issued a forecast for the firm after school closures. These observations are excluded from the sample. In the example, Firm A announced earnings before school closures, and Analyst X (Y) issued a forecast for Firm A after (before) the school closures.

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[9] Excluding analysts whose children's ages cannot be estimated from the sample does not change the results.

[10] The example in Fig. 1 assumes that Analysts X and Y have the same school closure dates. The school closure timing differs when analysts following the same firm are in different states. Relaxing this assumption does not change the sample screening criteria.

[11] Table IA1 in the internet appendix presents the baseline results when the type of Analyst X's forecast is classified as the treatment group. The findings confirm the upward bias in the negative effect of school closures on forecast timeliness. The main results on gender differences are robust to using this alternative definition of the treatment group.

schools were mandated to close during the COVID-19 pandemic as well. According to Zviedrite et al. (2021), government policies in 19 states specifically mandated the closure of private schools.[12] The mandated school closures during the COVID-19 pandemic influenced at least 9700 private schools serving over 1.6 million students.

2.2. Variable definitions

2.2.1. Forecast timeliness

Following the literature on analyst forecast timeliness (Zhang (2008); Driskill et al. (2020); Chiu et al. (2021)), I define a dummy variable $Timely_{i,j,t}$, which is equal to one if analyst j issues the forecast for the earnings of firm i in quarter $t+1$ within one trading day (day 0 or day 1) after the earnings announcement of firm i for quarter t and zero otherwise.

2.2.2. Forecast accuracy

To measure forecast accuracy, I first calculate the absolute forecast error as the absolute value of the difference between the analyst earnings forecast and the actual earnings announced by the firm. Following Clement and Tse (2005), I define *Forecast accuracy* as:

$$Forecast\ accuracy_{i,j,t} = \frac{Absolute\ forecast\ error\ Max_{i,t} - Absolute\ forecast\ error_{i,j,t}}{Absolute\ forecast\ error\ Max_{i,t} - Absolute\ forecast\ error\ Min_{i,t}} \quad (1)$$

where *Absolute forecast error Min$_{i,t}$* and *Absolute forecast error Max$_{i,t}$* are the minimum and maximum of the absolute forecast errors for all analysts following firm i in quarter t issued in the same 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, compared to the forecasts for the earnings of the same firm in the same quarter issued in the same month.

2.3. Summary statistics

Table 1 reports statistics on variables used in the main analyses in the sample of analysts who are identified as having children (the main sample). Panel A shows that 12% 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 20 firms in the quarter, works in a brokerage with 46 analysts, and has 27 quarters of firm-specific experience.

Panel B of Table 1 shows the difference between mother analysts and father analysts. t-statistics are based on univariate regressions of the variables on the female indicator, and standard errors are clustered by analyst and firm. For most variables, the difference between father and mother analysts is statistically insignificant. The modest difference between gender is expected, given that only competitive women self-select into the financial analyst profession. Nevertheless, I control for variables that are expected to affect analyst forecasts in the analyses.

Fig. 2 plots the proportion of timely forecasts in the forecasts of father and mother analysts over a nine-week event window surrounding the exogenous shock to childcare demands. It shows that the forecast timeliness is trending closely in parallel for father and mother analysts in the four weeks before the school closures. Mother analysts issue more timely forecasts than father analysts before school closures. This may be explained by self-selection, as suggested in Kumar (2010): only competent female analysts select to work in this male-dominated industry, and they possess better-than-average skills for issuing accurate and timely forecasts. The figure shows that the forecast timeliness of both mother and father analysts decreases right in the week of the school closure announcements, but the negative effect is larger and lasts longer for mother analysts.

3. The effect of school closures on mother analysts' forecasts

3.1. The effect of school closures on forecast timeliness

I test the effect of childcare responsibilities on analysts' forecast timeliness by exploring the exogenous school closure decisions during the COVID-19 pandemic in the following linear probability model:

$$Timely_{i,j,t} = \alpha + \beta_1\ School\ closure_{i,j,t} \times Female_j + \beta_2\ School\ closure_{i,j,t} + \beta_3\ Female_j + Controls + u_i + v_j + z_t + \varepsilon_{i,j,t}, \quad (2)$$

where *School closure$_{i,j,t}$* indicates whether schools are closed in the state of analyst j when the analyst issues forecasts for firm i in quarter t; *Female$_j$* is a dummy variable equal to one if the analyst is a female and zero otherwise. The regression includes

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[12] In addition, four states and the District of Columbia ordered the closure of private schools via stay-at-home orders. 10 other states recommended private school closures directly or effectively enforced private school closures via stay-at-home orders.

Table 1
Summary statistic.

Panel A: Summary statistics of variables						
Variable	Obs	Mean	Std. Dev.	P25	Median	P75
Female	4,726	0.12	0.33	0	0	0
School closure	4,726	0.64	0.48	0	1	1
Timely	4,726	0.78	0.41	1	1	1
Forecast lag	4,726	2.55	7.53	0	1	1
Concurrent earnings announcements	4,726	0.99	1.35	0	1	1
No. of firms followed	4,726	19.68	7.65	14	19	24
Broker size	4,726	45.78	30.39	20	46	62
Experience in the firm	4,726	26.72	24.76	8	20	38
Firm size	4,726	14.97	2.71	13.76	15.19	16.74
Institutional ownership	4,726	0.71	0.24	0.58	0.78	0.89
Book to market	4,726	0.56	0.49	0.2	0.43	0.8
Bad earning news	4,726	0.33	0.47	0	0	1
Special items	4,726	0.66	0.47	0	1	1
Log number of following analysts	4,726	2.66	0.55	2.3	2.71	3.04
Forecast accuracy	4,382	0.56	0.36	0.24	0.6	0.89
Childcare-intensive time	5,424	0.33	0.47	0	0	1

Panel B: Comparison of variables between gender								
Variable	Male			Female			Diff	t-statistics
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.		
Timely	4,146	0.778	0.416	580	0.817	0.387	−0.039	−0.94
Concurrent earnings announcements	4,146	0.943	1.288	580	1.305	1.679	−0.362	−1.45
No. of firms followed	4,146	19.565	7.794	580	20.514	6.443	−0.949	−0.74
Broker size	4,146	45.229	30.645	580	49.728	28.246	−4.498	−0.88
Experience in the firm	4,146	26.561	24.805	580	27.838	24.459	−1.277	−0.44
Firm size	4,146	14.987	2.721	580	14.812	2.592	0.174	0.85
Institutional ownership	4,146	0.714	0.241	580	0.684	0.236	0.030	1.58
Book to market	4,146	0.551	0.497	580	0.631	0.448	−0.081	−1.52
Bad earning news	4,146	0.315	0.465	580	0.395	0.489	−0.080	−1.26
Special items	4,146	0.668	0.471	580	0.595	0.491	0.073	1.23
Log number of following analysts	4,146	2.673	0.541	580	2.527	0.570	0.146	1.70
Forecast accuracy	3,853	0.560	0.358	529	0.522	0.376	0.038	1.54
Childcare-intensive time	4,790	0.329	0.470	634	0.347	0.476	−0.018	−0.61

This table contains summary statistics. Panel A contains the number of observations (Obs), mean, standard deviation (Std. Dev.), 25% percentile (P25), median, and 75% percentile (P75) in the sample of analysts who are identified as having children (the main sample). Panel B contains the difference in the value of variables for father and mother analysts. *t*-statistics are based on univariate regressions of the variables on the female indicator, and standard errors are clustered by analyst and firm. All variables are defined in Appendix B.

firm fixed effects, analyst fixed effects, and time fixed effects to control for time-invariant characteristics of firms and analysts, and the time trend. Including analyst fixed effects takes care of any general capability, work habits, work experience, personality traits, and demographics that may impact the likelihood of issuing timely forecasts. Heteroscedasticity-adjusted robust standard errors are used.

Table 2 contains the regression results. In the model controlling for firm, broker, state, and time fixed effects (Column (1)), mother analysts' forecast timeliness decreases at a 12.9 pp larger magnitude than that of father analysts after school closures, and the gender difference is statistically significant at the 1% level. After controlling for time-invariant characteristics of analysts by adding analyst fixed effects (Column (2)), the coefficient estimate of the interaction term of *Female* and *School closure* rises to 13.6 pp, which is statistically significant at the 1% level. The difference is economically significant, given that it accounts for 17.4% of the average forecast timeliness in the sample (i.e., 0.78 in Panel A of Table 1). The results hold after controlling for firm × quarter fixed effects (Column (3)).[13] The model is very strict because it controls for all time-varying firm characteristics that may influence analyst forecasts. After school closures, the forecast timeliness of mother analysts decreases by 11.4 pp more than that of father analysts who issue the forecasts for the same firm in the same quarter.

The coefficient estimates of the school closure indicator range from −4.9 pp to −6.9 pp and are statistically insignificant in all model specifications. The results indicate that father analysts do not issue less timely forecasts after school closures.[14] As for the control variables, several of them significantly influence forecast timeliness. Consistent with the findings of Driskill et al. (2020), the number of concurrent earnings announcements has a negative effect on forecast timeliness. In addition,

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[13] The number of observations varies in different model specifications because different numbers of singletons are dropped depending on the fixed effects in the models.

[14] The coefficient estimates of the school closure indicator need to be interpreted with caution. The school closures may co-mingle with other events during the COVID-19 outbreak, and all confounding effects are captured in these coefficient estimates. Even though the school closures are staggered, strictly speaking, the model specifications cannot disentangle potential confounding effects from the school closures for father analysts as a control group.
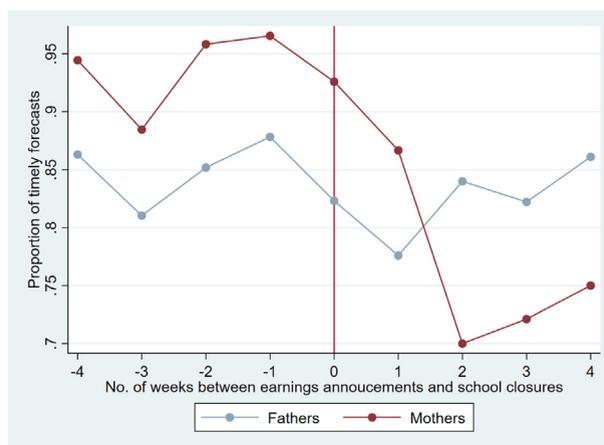
Fig. 2. Forecast timeliness of father and mother analysts' earnings forecasts around the COVID-19 school closures. This figure plots the proportion of timely forecasts in forecasts of male analysts and female analysts who are identified as having children four weeks before and four weeks after the COVID-19 school closures. The proportion of timely forecasts is calculated as the number of timely forecasts scaled by the total number of forecasts.

Table 2
COVID-19 school closures and the forecast timeliness of mother analysts.

Dependent variable:	Timely		
	(1)	(2)	(3)
School closure × Female	−0.129***	−0.136***	−0.114***
	(-3.71)	(-3.63)	(-2.89)
School closure	−0.049	−0.065	−0.069
	(-0.64)	(-0.93)	(-0.96)
Female	0.085***		
	(2.93)		
Concurrent earnings announcements	−0.014*	−0.011	−0.008
	(-1.83)	(-1.47)	(-0.97)
Firm size	−0.005	−0.004	
	(-0.36)	(-0.35)	
Institutional ownership	0.000	0.014	
	(0.00)	(0.03)	
Book to market	0.016	0.021	
	(0.37)	(0.50)	
Bad earning news	−0.012	−0.029	
	(-0.36)	(-0.87)	
Special items	0.045	0.057	
	(0.43)	(0.58)	
Log number of following analysts	0.170	0.123	
	(1.11)	(0.85)	
No. of companies followed	0.005***	0.002	0.002
	(4.33)	(1.23)	(0.60)
Broker size	0.003	0.001	0.001
	(0.90)	(0.73)	(0.31)
Experience in the firm	0.001***	0.001*	0.001*
	(2.88)	(1.95)	(1.95)
Fixed effects	Firm, Broker, State, Time	Firm, Analyst, Time	Firm-quarter, Analyst, Time
Observations	4,726	4,700	4,559
Adjusted R^2	0.346	0.444	0.456

This table contains the regression results of *Timely* on *School closure, Female*, and their interaction term in the sample of analysts with children. *Timely* is a dummy variable equal to one, if the analyst issues an earnings forecast for quarter *t* 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. Heteroscedasticity-adjusted robust standard errors. *t*-statistics are provided in parentheses. * * *, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

analysts with more experience in issuing forecasts for the firm are more likely to issue timely forecasts. The number of firms followed by an analyst is also positively related to forecast timeliness, but the effect becomes insignificant after controlling for analyst fixed effects.

A potential problem of exploring the state-level school closures in the setting of financial analysts is that many analysts are located in New York, where life differs from that in other states in many ways. In the sample, a larger proportion of the female

analysts is located in New York (66%), compared to that of male analysts (52%). If the forecast timeliness of the analysts in New York is more likely to decrease after the COVID-19 pandemic than that of the analysts in other states because of the limited space when working from home, the gender difference in the school closure effects may capture the geographical difference. To control for this geographical effect, I include state fixed effects and analyst fixed effects in the analyses. Table IA2 in the internet appendix shows that the baseline results are robust in the sample excluding analysts in New York. The findings confirm that the baseline results are not driven by the geographical difference in, for example, the workspace at home.

I further investigate how the school closure effects differ for analysts with children at different ages. As described in Section 2.1, I can collect information of the ages of the youngest children for 266 analysts based on Facebook posts: 75 have children under six years old, 161 have children between six and 18, and 30 have children older than 18 years old. Fig. 3 plots the coefficient estimates of *School closure* in the linear probability regressions of *Timely* on *School closure* in the samples of male or female analysts with children under six, between six and 18, and older than 18 years old, respectively. The regressions control for analyst fixed effects and use heteroscedasticity-adjusted robust standard errors.

The results show that the forecast timeliness of female analysts with children from six to 18 years old decreases the most, by 19 pp, among all mother analysts after school closures. The decrease is larger than that of female analysts with children younger than six (9 pp). The potential reason is that the treatment of the COVID-19 school closures better captures the increase in childcare responsibilities for mothers of children between six and 18 years old. By contrast, female analysts with adult children are not influenced by school closures: the effect of school closures on their forecast timeliness statistically insignificant at the conventional level. These results confirm that the effect of the COVID-19 school closures on forecast timeliness is likely to be explained by the increase in childcare responsibilities, instead of other factors associated with school closures, such as the number of COVID-19 cases in the states, because factors other than the increase in the childcare responsibilities after school closures are expected to similarly affect female analysts with children at different ages. As with male analysts, only those with children younger than six have a 7 pp lower forecast timeliness after school closures.

There are several caveats in the interpretation of the analysis of the sample split based on the ages of children because of data limitations. First, given the limited number of observations in each group, it is impossible to run the same linear probability models with control variables and high-dimensional fixed effects. Second, there may be inaccuracies in the estimation of children's ages based on Facebook posts. Even though I cross-validate three research assistants' independent age estimates based on Facebook posts, there is no other data source to validate the data quality due to the scarcity of data on personal information. Nevertheless, inaccuracy in age estimation is more likely to introduce noise rather than bias in the data analysis. Overall, these findings help attribute the effect of school closures on mother analysts to childcare responsibilities because the effect is the most prominent among mother analysts with school-age children.
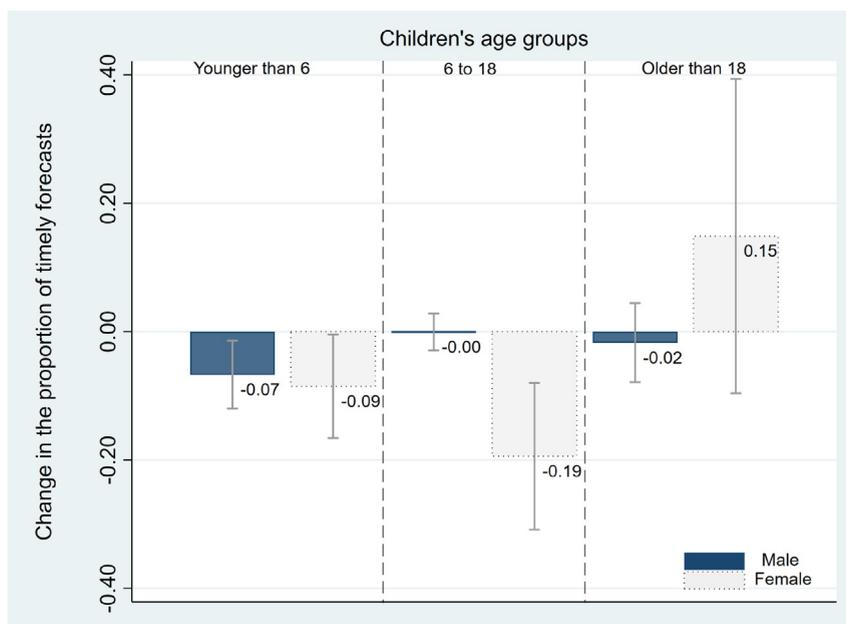

Fig. 3. Children age and the school closure effects. This figure plots the coefficient estimates of *School closure* in the regression of *Timely* on *School closure* in sub-samples of male or female analysts with children under six years old, between six and 18 years old, and older than 18 years old, respectively. All regressions control for analyst fixed effects. Heteroscedasticity-adjusted robust standard errors are used. The confidence intervals of the coefficient estimates are at the 90% level.

Table 3

COVID-19 school closures and the forecast accuracy of mother analysts.

Dependent variable:	Forecast accuracy		
	(1)	(2)	(3)
School closure × Female	−0.045	−0.064	−0.077*
School closure	(-1.10)	(-1.50)	(-1.68)
School closure	−0.057	−0.084	−0.078
	(-0.53)	(-0.84)	(-0.78)
Female	0.029		
	(0.78)		
Control variables	Yes	Yes	Yes
Fixed effects	Firm, Broker, State, Time	Firm, Analyst, Time	Firm-quarter, Analyst, Time
Observations	4,382	4,357	4,200
Adjusted R^2	0.100	0.128	0.151

This table contains the regression results of *Forecast accuracy* on *School closure, Female*, and their interaction term in the sample of analysts with children. *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 *Concurrent earnings announcements, 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. Heteroscedasticity-adjusted robust standard errors. *t*-statistics are provided in parentheses. * * *, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

3.2. The effect of school closures on forecast accuracy

In this section, I empirically investigate the effect of school closures on forecast accuracy. I run a regression of *Forecast accuracy* on the dummy variables *School closure*, *Female*, and their interaction terms, controlling for firm and analyst characteristics and various fixed effects as in Table 2. Heteroscedasticity-adjusted robust standard errors are used.

Table 3 contains the regression results. The effect of school closures on forecast accuracy is statistically insignificant in two out of three model specifications. Only after controlling for firm × quarter fixed effects, the effect is statistically significant at the 10% level. I do not find robust evidence that on average, mother analysts issue less accurate forecasts compared to father analysts after school closures.

In the next step, I explore how mother analysts make trade-offs regarding the accuracy of forecasts for firms in their coverage portfolios. Harford et al. (2019) find that analysts issue more accurate forecasts for firms that are more important for their careers. Hence, after the COVID-19 school closures, mother analysts may prioritize maintaining the forecast accuracy for these sorts of firms.

Following Harford et al. (2019), I measure the importance of a firm in an analyst portfolio based on its institutional ownership because analysts tend to cater for institutional investors to gain favorable outcomes in their careers. For each analyst-earnings announcement date, I rank the institutional ownership of firms in the analyst's coverage portfolio and define firms as having high institutional ownership if they are in the top quintile of portfolio firms issuing forecasts on the same day in terms of institutional ownership.[15] I run a regression of *Forecast accuracy* on the dummy variables *School Closure*, *Female*, and their interaction term in the sub-samples of forecasts for firms with relatively high and low institutional ownership, respectively. The control variables and fixed effects are the same as in Table 3.

Table 4 presents the regression results. The coefficients estimates of the interaction term between the female indicator and school closure indicator are negative and statistically significant at the 10% level for firms with relatively low institutional ownership. This means that, for firms that are relatively less important for the analysts' careers, mother analysts' forecast accuracy reduces by around 10 pp, that is, around 17.8% of the average forecast accuracy in the sample, after the school closures. By contrast, school closures have no effect on mother analysts' forecast accuracy for firms with relatively high institutional ownership. The findings indicate that mother analysts maintain forecast accuracy for firms that are important for their careers.[16]

To summarize, after the COVID-19 school closures, mother analysts decrease the accuracy of forecasts for firms with relatively low institutional ownership but do not change the accuracy level of forecasts for firms with relatively high institutional ownership.

3.3. The effect of school closures on forecast release time

Analysts have busy schedules (Bradshaw et al. (2017)) and have some autonomy in choosing the time of day when they release earnings forecasts. However, little is known about what influences the time of day when they do so. This section investigates the effect of the COVID-19 school closures on the forecast release time.

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[15] Results are robust to defining the high institutional ownership as in the top quartile or decile.

[16] Similar analyses on forecast timeliness also find that the decrease in mother analysts' forecast timeliness after school closures is larger for firms with low institutional ownership (see Table IA3 in the Internet Appendix).

Table 4

COVID-19 school closures and the forecast accuracy of mother analysts - Cross-sectional tests based on institutional ownership.

	Forecast accuracy			
	(1)	(2)	(3)	(4)
Dependent variable:	Low IO	High IO	Low IO	High IO
School closure × Female	−0.096*	0.018	−0.108*	−0.001
	(-1.77)	(0.20)	(-1.87)	(-0.01)
School closure	−0.100	0.040	−0.111	0.034
	(-0.52)	(0.15)	(-0.55)	(0.13)
Control variables	Yes	Yes	Yes	Yes
Fixed effects	Firm, Analyst, Time	Firm, Analyst, Time	Firm-quarter, Analyst, Time	Firm-quarter, Analyst, Time
Observations	3,086	899	2,934	835
Adjusted R^2	0.140	0.214	0.163	0.202

This table contains the regression results of *Forecast accuracy* on *School closure*, *Female* and their interaction term in sub-samples divided by institutional ownership. *High IO* (institutional ownership) indicates the firm is in the top quintile of an analyst's portfolio firms in terms of institutional ownership. Control variables include *Concurrent earnings announcements*, *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. Heteroscedasticity-adjusted robust standard errors. *t*-statistics are provided in parentheses. * * *, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

The forecast release time is obtained from I/B/E/S.[17] I transfer the data based on the Eastern Standard Time zone to local time based on the state where the analyst is located.[18] Fig. 4 plots the distribution of the forecast release time of the day before and after the school closures in the sample of father analysts (Panel A) and mother analysts (Panel B), separately. As expected, after school closures, the fraction of forecasts released by mother analysts decreases during hours when childcare demands, such as homeschooling and cooking, are high (highlighted hour intervals in the figure). By contrast, the change in the forecast release time for father analysts after school closures is not as significant.

In the next step, I formally test whether mother analysts are less likely to release forecasts during the periods of a day when childcare work is intensive in regressions. I define *Childcare-intensive time* as a dummy variable equal to one if analyst *j* releases the earnings forecast for firm *i* during the time of a day when childcare demands are high, that is, from 7:00 to 9:00, from 12:00 to 14:00, and from 17:00 to 21:00 and zero otherwise. Based on the summary statistics in the Panel A of Table 1, 33% of the analyst forecasts in the sample are released during the childcare-intensive periods.

I run a regression of *Childcare-intensive time* on *School closure*, *Female*, and their interaction term, controlling for firm, brokerage, state (or analyst), and forecast time fixed effects. Considering the potential difference in earnings announcement time, I also control for earnings announcement time fixed effects. I include analyst characteristics, the number of firms in the coverage, brokerage size, and analysts' experience in the firm, because these characteristics may influence the time of day an analyst releases forecasts. Table 5 contains the regression results. After school closures, mother analysts are around 10 pp less likely to release forecasts during childcare-intensive hours compared to father analysts. The difference accounts for around 30% of the average *Childcare-intensive* in the sample. On the contrary, father analysts do not significantly shift the time of day when they release forecasts.

Taking advantage of the detailed timestamps of analysts' forecasts, I show that, after the school closures, mother analysts shift their forecast releases to hours when childcare demands are less likely to be intensive. This result provides additional evidence that the COVID-19 school closures influenced mother analysts more than father analysts.

4. Extensions to the sample of all analysts: gender differences in school closure effects

The analyses in this section extend to all financial analysts in the I/B/E/S sample, regardless of whether they have children. The sample in the previous section may drop out analysts who have children but are falsely identified as not having them because they cannot be found on Facebook or thatsthem.com. The analyses in this section provide complementary evidence on the gender difference in the school closure effects on analyst forecasts. The obvious disadvantage of using the sample of all analysts is that the estimated gender difference does not accurately capture the effect of school closures on analyst forecasts. These analyses may underestimate the treatment effect, potentially giving rise to attenuation bias, because child-rearing duties are critical for the school closure effect. Therefore, I expect to observe a smaller negative effect of school closures on female analysts' productivity in this sample.

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[17] Based on the interpretation by the data provider, the variable announcement time (ANNTIMS) from I/B/E/S 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 earnings feeds. The timestamp "00:00:00" may be missing values, so I exclude the observations (only 133) from the sample.

[18] 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 zone so 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.
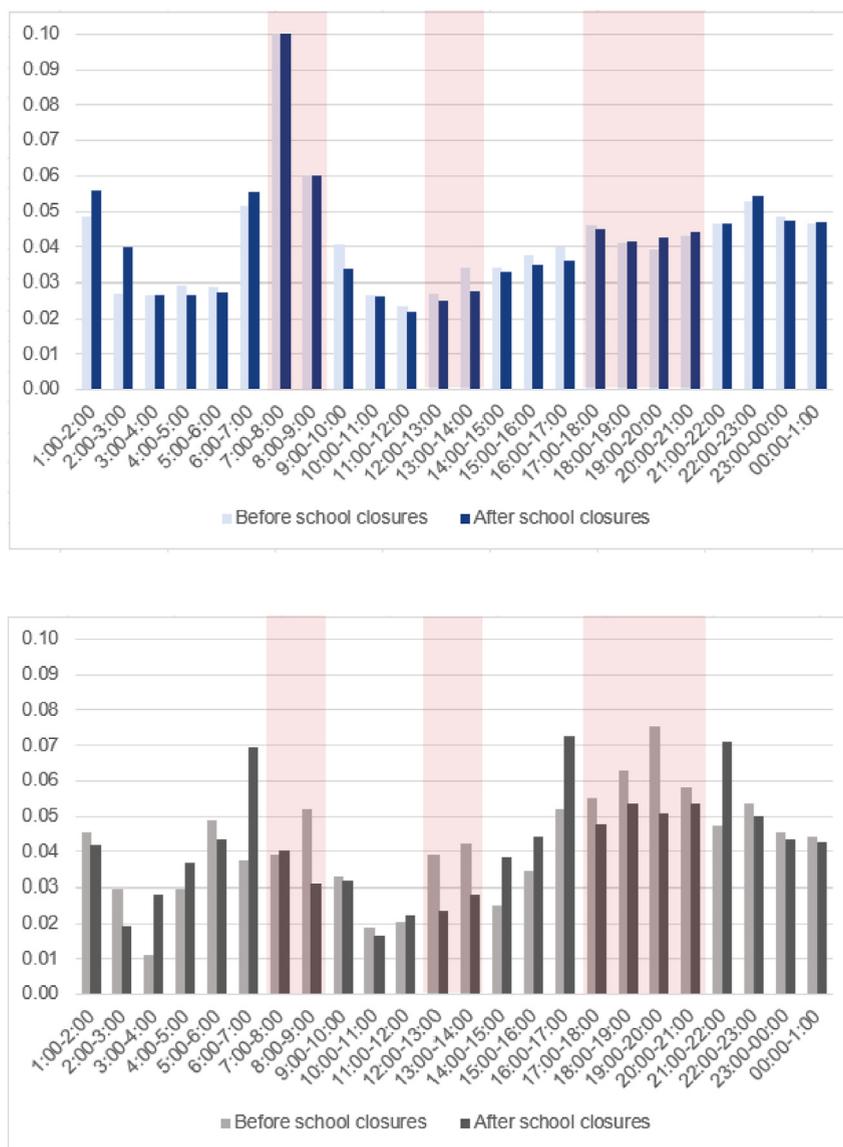
Fig. 4. COVID-19 school closures and the distribution of forecast release time. This figure plots the fraction of earnings forecasts released by analysts with children during each hour interval of the day before and after the COVID-19 school closures. Panel A contains the distribution of forecast release time among father analysts (male analysts with children). Panel B the distribution of forecast release time among mother analysts (female analysts with children). The hour intervals during which the childcare demands are high (7:00 to 9:00, 12:00 to 14:00, and 17:00 to 21:00) are highlighted.

Panel A of Table 6 contains the regression results of the linear probability model in Equation (2) in the sample of all analysts. Female analysts' forecast timeliness decreases at a 6.7 pp larger magnitude than that of male analysts after school closures in the model with firm, analyst, and time fixed effects. The gender difference is statistically significant at the at least 10% level across different model specifications. The findings confirm that female analysts, in general, are less likely to issue timely forecasts after COVID-19 school closures than male analysts. The economic magnitude of the gender difference in the whole sample amounts to 8.7% of the average forecast timeliness in the sample, which is smaller than that in the sample of analysts with children.[19,20]

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[19] The average of *Timely* is 0.77 (untabulated) in the sample of all analysts.

[20] Similar findings are obtained in the analyses of forecast accuracy and forecast release time in the sample of all analysts (See Tables IA4 and IA5 in the internet appendix).

Table 5
COVID-19 school closures and the forecast release time of mother analysts.

Dependent variable:	Childcare-intensive time		
	(1)	(2)	(3)
School closure × Female	−0.091*	−0.099*	−0.101**
	(-1.93)	(-1.95)	(-1.97)
School closure	−0.020	0.087	0.083
	(-0.96)	(0.62)	(0.58)
Female	0.068		
	(1.55)		
No. of companies followed			0.002
			(0.29)
Broker size			0.001
			(0.28)
Experience in the firm			−0.001
			(-1.13)
Fixed effects	Firm, Broker, State, EA time Forecast time	Firm, Analyst, EA time Forecast time	Firm-quarter, Analyst, EA time Forecast time
Observations	5,424	5,371	5,282
Adjusted R^2	0.093	0.166	0.169

This table contains the regression results of *Childcare-intensive time* on *School closure*, *Female,* and their interaction term in the sample of analysts with children. *Childcare-intensive time* is a dummy variable equal to one if analyst *j* releases the earnings forecast for firm *i* during the time of a day when childcare demands are high, that is, from 7:00 to 9:00, from 12:00 to 14:00, and from 17:00 to 21:00 and zero otherwise. All variables are defined in Appendix B. Heteroscedasticity-adjusted robust standard errors. *t*-statistics are provided in parentheses. * * *, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

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 of 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.

An alternative explanation for the baseline findings could be that female analysts are more risk-averse (e.g., Powell and Ansic (1997)) and less overconfident (e.g., Lenney (1977); Barber and Odean (2001)) than male analysts so they delay their forecasts more than male analysts after the outbreak of the pandemic. In that case, female analysts without children would delay their forecasts more than male analysts without children after the COVID-19 school closures as well. To compare the school closure effects between the analysts who are identified as having children and the rest, I conduct a triple difference estimation by adding interaction terms among *School closure*, *Female*, and *Having children* to the model of Equation (2) with the sample of all analysts.

Panel B of Table 6 shows the results. Mother analysts' forecasts are around 10 pp less timely after school closures, which accounts for around 13% 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 at least 10% level in all model specifications. The statistically insignificant coefficient estimates of the interaction term between *School closure* and *Female* indicate that female analysts without children do not issue less timely forecasts after school closures, compared to their male counterparts. Hence, the documented school closure effects among mother analysts relative to those among father analysts cannot be explained by gender differences in risk aversion or overconfidence.

5. Additional analyses and robustness checks

5.1. The gender difference in the effect of H1N1 school closures

In this section, I examine the effect of another massive school closure event on analyst forecasts to confirm the generalizability of baseline findings. During the H1N1 pandemic in 2009, approximately 200 schools closed, which affected an estimated 80,000 students.[21] However, it is hard to capture the effect of these school closures because the decisions were inconsistent and dispersed (Klaiman et al. (2011)), unlike the school closure decisions during the COVID-19 pandemic.[22]

I try to estimate H1N1 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 at different times across the year 2009, that is, 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 that other states opened schools (Klaiman et al.

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[21] See www.publicschoolreview.com/blog/will-your-childs-school-shut-down-to-prevent-the-spread-of-h1n1

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

Table 6
COVID-19 school closures and forecast timeliness - The gender difference in the sample of all analysts.

Panel A: Gender difference analysis Dependent variable:	Timely		
	(1)	(2)	(3)
School closure × Female	−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)		
Control variables	Yes	Yes	Yes
Fixed effects	Firm, Broker, State, Time	Firm, Analyst, Time	Firm-quarter, Analyst, Time
Observations	15,208	15,088	15,050
Adjusted R^2	0.292	0.428	0.429
Panel B: Triple difference analysis Dependent variable:	Timely		
	(1)	(2)	(3)
School closure × Female × Having children	−0.107***	−0.096**	−0.072*
	(-2.61)	(-2.29)	(-1.69)
School closure × Female	−0.003	−0.029	−0.034
	(-0.09)	(-1.10)	(-1.29)
School closure × Having children	0.008	0.009	0.005
	(0.57)	(0.67)	(0.33)
Female × Having children	0.069		
	(1.08)		
School closure	−0.067**	−0.036	−0.039
	(-2.45)	(-1.20)	(-1.29)
Female	0.012		
	(0.56)		
Having children	−0.004		
	(-0.40)		
Control variables	Yes	Yes	Yes
Fixed effects	Firm, Broker, State, Time	Firm, Analyst, Time	Firm-quarter, Analyst, Time
Observations	15,208	15,088	15,050
Adjusted R^2	0.293	0.429	0.434

This table contains the analyses in the sample of all analysts. Panel A contains the regression results of *Timely* on *School closure*, *Female,* and their interaction term. Panel B contains the regression results of *Timely* on *School closure*, *Female*, *Having Children*, and their interaction terms. Control variables include *Concurrent earnings announcements*, *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. Heteroscedasticity-adjusted robust standard errors.
* * *, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

(2011)), comparing the difference in forecast timeliness between New York analysts and non-New York analysts in May and June 2009. The sample of the analysis in this section covers all analysts regardless of whether they have children or not because it is harder to obtain personal information on analysts in the earlier sample period.

Table 7 contains the regression results. Female analysts are 2 pp less likely to issue timely forecasts in 2009 when school closures happened, compared with their 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 forecasts 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 becomes statistically significant at the 10% level when control variables are added (Column (4)), but the economic level remains similar. The findings further confirm the baseline results that female analysts are less likely to issue timely forecasts after unexpected school closures caused by pandemics.

5.2. The gender difference in the effect of financial crises

The time of the COVID-19 school closures overlaps with a financial crash. Might female analysts' forecast timeliness be negatively influenced by the financial crash instead of the school closures? If female analysts are more risk-averse and less overconfident (e.g., Powell and Ansic (1997); Lenney (1977); Barber and Odean (2001)), they may be more likely to postpone forecast releases because of the financial crash in March 2020. In this section, I conduct a test on the gender difference in forecast timeliness during financial crises to examine whether there is any gender difference in the effect of financial crises with no school closure on analyst forecasts.

Based on the NBER definition of the financial crisis, there were 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, I use the sample period from 2000 to 2002 and the sample period from 2007 to 2010, respectively. Table 8 presents the results. The financial crisis in 2001 does not have a significant effect on forecast

Table 7

H1N1 school closures and forecast timeliness.

Dependent variable:	Timely			
	(1)	(2)	(3)	(4)
Counterfactual	2009 vs 2008 and 2010		New York vs other states in May and June 2009	
H1N1 school closure × Female	−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	190,147	199,488	8,085	7,563
Adjusted R^2	0.252	0.334	0.432	0.415

This table contains the regression results of *Timely* on *H1N1 school closure*, *Female*, 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* within one trading day (day 0 or day 1) after the firm's quarter *t* earnings announcement date and zero otherwise. Control variables include *Concurrent earnings announcements*, *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. Heteroscedasticity-adjusted robust standard errors. *t*-statistics are provided in parentheses. * * *, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8

Financial crises and forecast timeliness.

Dependent variable:	Timely			
	(1)	(2)	(3)	(4)
Financial crisis:	2001		2007−2009	
Financial crisis × Female	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	127,681	152,609	255,772	288,442
Adjusted R^2	0.198	0.308	0.243	0.331

This table contains the regression results of *Timely* on *Financial crisis*, *Female*, 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* within one trading day (day 0 or day 1) after the firm's quarter *t* earnings announcement date and zero otherwise. Control variables include *Concurrent earnings announcements*, *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. Heteroscedasticity-adjusted robust standard errors. *t*-statistics are provided in parentheses. * * *, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

timeliness, while the more severe financial crisis in 2008 is associated with a decrease in the likelihood of analysts issuing timely forecasts by more than 20 pp. In contrast to the gender difference in the negative effect of school closures on forecast timeliness, the negative effect of the 2008 financial crisis is not more salient among female analysts. 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 and analyst fixed effects are controlled for. The results indicate that the gender difference in the effect of the COVID-19 school closures on analyst forecasts is not likely to be driven by the contemporaneous financial crash.

5.3. Robustness checks

Table IA6 in the internet appendix contains the robustness tests of the baseline results in Table 2. The results are robust to choices of sample periods and various measures of forecast timeliness.

Panel A of Table IA6 shows that mother analysts issue less timely forecasts after school closures in the sample of forecasts in the short window around school closing decisions in March 2020, forecasts after school closures in 2020 and in respective

time periods in 2019, and forecasts from 1999 to 2020. Panel B of Table IA6 contains the analyses using different forecast timeliness measures as dependent variables. I define a continuous measure of forecast timeliness, *Forecast lag$_{i,j,t}$*, as the number of trading days between the earnings announcement date of firm i for quarter t and the date when analyst j releases the forecast for the earnings of firm i in quarter $t+1$. Columns (1) to (3) in the Panel B of Table IA6 use *Forecast lag*, the log form of *Forecast lag*, and an indicator of whether analysts issue forecasts within three trading days after the earnings announcement as dependent variables, respectively. The results are robust to using all these measures of forecast timeliness.

6. Conclusion

This paper is the first to investigate how the productivity of financial analysts is associated with childcare responsibilities using an exogenous shock of the COVID-19 school closures. I find strong and robust evidence that mother analysts issue less timely forecasts, compared to father analysts, after the COVID-19 school closures but maintain forecast accuracy for firms that are more important for their careers. In addition, after school closures, they shift their forecast release time to hours when they are less likely to be occupied with childcare.

The findings indicate that the COVID-19 school closures, which are likely to increase childcare responsibilities at home, disproportionately influenced the work productivity of mother analysts, even though they are high-achieving women who have established themselves in a male-dominated industry. On the bright side, the findings imply that the gender pay gap and occupational gender segregation in the labor market may be able to be lessened by alleviating the imbalance in childcare responsibilities between the genders or by providing better external childcare services.

The findings also have policy implications. COVID-19-induced measures, such as school closures and stay-at-home orders, influenced different groups unequally and have intensified the challenges that working mothers face in the workplace. As found in this paper, even high-achieving women were vulnerable to COVID-19-related social effects.

Previous literature has examined gender differences in career and childcare choices. Hakim (2000) argues that women's lifestyle preferences are the main determinants of their choices between an emphasis on family life and career success. Recent research (e.g., Bursztyn et al. (2017) and Barigozzi et al. (2018)) emphasizes the role of social norms in shaping women's choices. This paper shows that women take more childcare responsibilities than men who have made the same career choice, which raises questions that are worth further investigation. Why do childcare responsibilities hurt the productivity of mother analysts more than that of father analysts? Do female analysts choose to take more childcare responsibilities based on their preferences or do they have to shoulder more childcare responsibilities under the pressure of social norms? I leave these questions for future research.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jacceco.2023.101603.

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, the earlier school closures caused by the COVID-19 pandemic started.

Created with mapchart.net
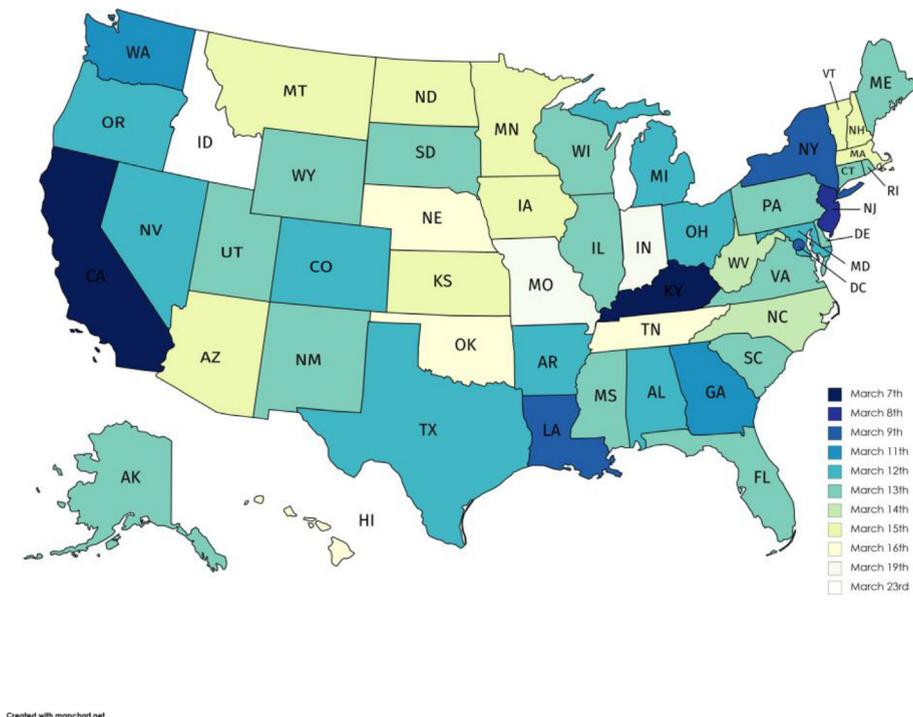
B Variable description.

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, including Facebook posts and thatsthem.com
3. CRSP: CRSP stock price data
4. Compustat: Compustat quarterly financial statement data
5. TR: Thomson Reuters Institutional (13f) Holdings
6. Call: Earnings conference transcripts from Seeking Alpha
7. MC: Manually constructed

Table. 1A

Variable name	Description	Data Source
Absolute forecast error$_{i,j,t}$	The absolute value of the difference between the an-alyst earnings forecast and the actual earning an- nounced by the firm.	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 fore- cast 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
Childcare-intensive time$_{i,j,t}$	Dummy variable equal to one if analyst j releases the earnings forecast for firm i during the time of a day when childcare demands are high, that is, from 7:00 to 9:00, from 12:00 to 14:00, and from 17:00 to 21:00 and zero otherwise.	IBES,MC
Concurrent earnings announcements$_{i,j,t}$	The number of followed firms' earnings announce-ments on the day when analyst j issues earnings fore- cast for firm i after its earnings announcement of quarter t.	IBES,MC

Table. 1A (*continued*)

Variable name	Description	Data Source
Experience in the firm$_{i,j,t}$	The number of quarters analyst j covers the forecast of firm i untile quarter t.	IBES,MC
Female$_j$	Dummy variable equal to one, if the analyst is female and zero otherwise.	IBES, Oinline,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
Forecast accuracy$_{i,j,t}$	Relative measure of the forecast accuracy calculated as in Equation (1).	IBES,MC

Table 2A

Variable name	Description	Data Source
Forecast lag$_{i,j,t}$	The number of days between a firm's current quarter earnings announcements and analyst forecasts for the next quarter.	IBES,MC
H1N1 school closure$_{i,j,t}$	Dummy variable equal to one, if schools in the state where analyst j is located are closed when firm i an- nounced its earnings announcement in 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 an analyst is iden- tified as having children based on Facebook posts or thatsthem.com and zero otherwise.	Online,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
No. of firms followed$_{j,t}$	The number of firms for which analyst j issues an earnings forecast in quarter t.	IBES,MC
Private school closure$_{i,j,t}$	Dummy variable equal to one, if private schools are closed in the states based on Zviedrite et al. (2021) and zero otherwise.	IBES, Online,MC
School closure$_{i,j,t}$	Dummy variable equal to one, if schools are closed in the state of analyst j when the analyst issues forecasts for firm i in quarter t and zero otherwise.	IBES, Online,MC
Special items$_{i,t}$	Dummy variable equal to one, if the special items reported by firm i are positive in quarter t and zero otherwise.	Compustat
Timely$_{i,j,t}$	Dummy variable equal to one, if analyst j issues the forecast for the earnings of firm i in quarter $t+1$ within one trading day (day 0 or day 1) after the earnings announcement of firm i for quarter t.	IBES,MC

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