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Analyst forecast accuracy during COVID-19: does prior epidemic experience matter?

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Abstract

Purpose – The authors examine the role of analysts' prior experience of forecasting for firms exposed to epidemics on analysts' forecast accuracy during the COVID-19 pandemic.

Design/methodology/approach – The authors examine the impact of analysts' prior epidemic experience on forecast accuracy by comparing the changes from the pre-COVID-19 period (calendar year 2019) to the post-COVID period extending up to March 2023 across HRE versus non-HRE analysts. The authors consider a full sample (194,980) and a sub-sample (136,836) approach to distinguish "Recent" forecasts from "All" forecasts (including revisions).

Findings – The study's findings reveal that forecast accuracy for HRE analysts is significantly higher than that for non-HRE analysts during COVID-19. Specifically, forecast errors significantly decrease by 0.6% and 0.15% for the "Recent" and "All" forecast samples, respectively. This finding suggests that analysts' prior epidemic experience leads to an enhanced ability to assess the uncertainty around the epidemic, thereby translating to higher forecast accuracy.

Research limitations/implications – The finding that the expertise developed through an experience of following high-risk firms in the past enhances analysts' performance during the pandemic sheds light on a key differentiator that partially explains the systematic difference in performance across analysts. The authors also show that industry experience alone is not useful in improving forecast accuracy during a pandemic – prior experience of tracking firms during epidemics adds incremental accuracy to analysts' forecasts during pandemics such as COVID-19.

Practical implications – The study findings should prompt macroeconomic policymakers at the national level, such as the central banks of countries, to include past epidemic experiences as a key determinant when forecasting the economic outlook and making policy-related decisions. Moreover, practitioners and advisory firms can improve the earning prediction models by placing more weight on pandemic-adjusted forecasts made by analysts with past epidemic experience.

Originality/value – The uncertainty induced by the COVID-19 pandemic increases uncertainty in global financial markets. Under such circumstances, the importance of analysts' role as information intermediaries gains even more importance. This raises the question of what determines analysts' forecast accuracy during the COVID-19 pandemic. Building upon prior literature on the role of analyst experience in shaping analysts' forecasts, the authors examine whether experience in tracking firms exposed to prior epidemics allows analysts to forecast more accurately during COVID-19. The authors find that analysts who have experience in forecasting for firms with high exposure to epidemics (H1N1, Zika, Ebola, and SARS) exhibit higher accuracy than analysts who lack such experience. Further, this effect of experience on forecast accuracy is more pronounced while forecasting for firms with higher exposure to the risk of COVID-19 and for firms with a poor ex-ante informational environment.

Keywords Analysts, COVID-19 outbreak, Past epidemics experience

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1. Introduction

Analysts play an instrumental role in disseminating accounting information by forecasting firm performance metrics, such as forecast future earnings, cash flows and stock prices for the firms they follow (Beneish, 1991; Dai *et al.*, 2021; Fosu *et al.*, 2018; Graaf, 2018; Luo *et al.*, 2022; O'brien, 1988; Wang *et al.*, 2022; Womack, 1996). Previous research looks at the role of prior experience and firm-specific characteristics as drivers of analysts' forecast properties (i.e. accuracy, dispersion). Brown and Mohammad (2010) document that analysts' earnings forecast ability and prior experience are incremental to firm-specific characteristics. However, Clement, Koonce, and Lopez (2007) argue that analysts' experience complements their knowledge of firm-specific characteristics. Both combined, they do improve the accuracy of forecasts. They also document a higher forecast accuracy for analysts with task-specific experience who exhibit strong innate abilities. Barron, Byard, and Yu (2008) find that individual analysts' private information helps them reduce errors and increase the accuracy of earnings forecasts. In this paper, we complement this stream of literature by examining the role of analysts' prior experience of forecasting for firms with greater exposure to risks of pandemics in shaping analysts' forecast accuracy during COVID-19. Investigating analysts' prior experience of forecasting for firms with greater exposure to risks of pandemics is essential for at least three appealing reasons.

First, COVID-19-induced uncertainty affects firms' fundamentals and analyst forecast characteristics. For instance, Southwestern Energy Co., operating in the natural gas and transmission industry, has high exposure to a pandemic, while EQT Corp., operating in the same industry, has negligible exposure to similar pandemics (Hassan *et al.*, 2020). This highlights that firms within the same industry have varying exposure to risks posed by epidemics. Thus, it is quite likely that the experience of following firms exposed to past pandemics varies in the cross section of analysts who follow firms in the same industry. This raises the possibility that industry experience alone could be an insufficient determinant of forecast accuracy during COVID-19. Sharma, Borah, and Moses (2021) study the role of governance structure, healthcare infrastructure and learning from past pandemics on what drives countries' responses to COVID-19. They show that learning from past pandemics and healthcare infrastructure positively impacts reactive and proactive strategies to combat COVID-19. Recently, Guo and Zhong (2023) have argued that analysts are considered experts in predicting industry growth and can serve as an external source of information for CEOs to learn about industry/segment growth opportunities. Thus, we posit that analysts following firms with higher exposure to epidemics would have gained differentiating skills and knowledge, resulting in a nuanced understanding of the idiosyncrasies of the firms' operations during the pandemic (Clement, 1999). Correspondingly, we expect analysts with prior epidemic experience, i.e. analysts with prior experience in tracking firms exposed to epidemics, such as H1N1, Ebola, SARS, etc. (HRE analysts, hereafter), can better comprehend and assess firms during the COVID-19 period. Also, there is a differential impact of COVID-19 within the same industry.

Second, while previous studies have extensively discussed analysts' role as information intermediaries, there is limited evidence on how the COVID-19 outbreak induced unparalleled uncertainty in capital markets. Maines, McDaniel, and Harris (1997) argue that the analysts' forecast accuracy level increases with experience. They show that experienced analysts' have higher forecast accuracy than less experienced ones. The setting of COVID-19 is an unpredictable event, and prior experience creates a clear motivation to learn lessons and make the necessary operational and cognitive adjustments (Lampel, Shasmsie, & Shapira, 2009). While experience has several connotations (general, firm-specific, pre-industry, etc.), industry experience is one of an analyst's most essential qualities (Bradley, Gokkaya, & Liu, 2017a, b). However, prior health experience plays a significant role during COVID-19, incremental to industry experience, as it enables analysts to forecast better than analysts who do not have such experience. Hence, whether analysts' past pandemic experiences matter for forecast accuracy remains an empirical unanswered research question.

Third, the environment of analyst forecasting has changed during the pandemic due to the extreme uncertainty brought by the pandemic in the capital markets. Reeves, Ramaswamy, and O'Dea (2022) have undertaken a meta-analysis of 20 forecasts for 2022 and beyond by prominent commentators and thought leaders on business and society [1]. They identify that social and economic forecasts exhibit the most significant divergence. The main reason is that forecasters must deepen into the unfamiliar world of epidemiology to understand the pandemic outbreak in each country better. Furthermore, macroeconomic forecasters gained lots of knowledge from past crises that could make the uncertainty of future economic crises less extreme.

We predict that prior experience of tracking firms during epidemics should allow analysts to forecast more accurately during COVID-19. Prior literature shows that analysts' experience influences forecast accuracy (Bradley *et al.*, 2017a; Clement, 1999; Guo *et al.*, 2020; Mikhail *et al.*, 1997). Pae & Yoon (2012) document that individual characteristics such as brokerage house size, the number of firms and industries followed and forecasting experience impact cash flow forecasts by analysts. In addition, Mikhail *et al.* (1997) base their argument on the "skilling-up by doing" model, i.e., analysts gain skills by repetitive forecasting for the same firms. They argue that with experience, the marginal cost of performing a task decreases. Hence, as effort becomes less costly through increased experience, analysts' accuracy improves (Lys & Soo, 1995).

However, several factors could dilute the impact of prior experience in driving the difference in the forecast accuracy of HRE and non-HRE analysts during COVID-19. For instance, prior epidemics, such as H1N1 and SARS, had limited consequences, unlike COVID-19 (Hassan *et al.*, 2020). Thus, experience gained from following firms with higher exposure to these pandemics might be less relevant to analysts during COVID-19. Moreover, analysts work harder during uncertain times (Loh & Stulz, 2018), which could substitute for the difference in experience between HRE and non-HRE analysts. Hence, the difference between the forecast accuracy of HRE and non-HRE analysts could be insignificant during COVID-19. Finally, analysts' spillover literature suggests inexperienced analysts tend to follow experienced analysts and attempt to forecast closer to the consensus forecasts during uncertainty (Cen *et al.*, 2020). Therefore, during COVID-19, non-HRE analysts could mimic HRE analysts leading to an insignificant difference in their forecast accuracy.

Based on the preceding discussion, it is evident that the impact of analysts' prior epidemic experience on forecast accuracy is unclear ex-ante. We create the base sample of our empirical analysis by merging Institutional Brokers Estimate System (I/B/E/S) for analyst-related information, Compustat for accounting and financial information and the data Hassan *et al.* (2020) provided for firm-level pandemics. This procedure results in a final sample of over 75,000 forecasts from January 2019 to March 2023. We consider a full sample (194,980) and a sub-sample (136,836) approach to distinguish "Recent" forecasts from "All" forecasts (including revisions). The "All" sample approach helps in accounting for spillover effects against analysts learning from each other during a particular forecast period (Cen *et al.*, 2020). We include firm and analyst fixed effects in our regression specifications to control time-invariant unobserved heterogeneity in our sample [2]. Hassan *et al.* (2020) use earnings call transcripts to identify the frequency of mention of words related to prior epidemics, such as H1N1, Ebola, Zika, SARS, etc. Based on this frequency, they assign a health exposure risk score to each firm in their sample. Using these data, we define prior epidemic experience as the history of forecasting for firms exposed to epidemics (Hassan *et al.*, 2020). Specifically, we define HRE analysts as those who follow firms with a demonstrated higher exposure to prior epidemics from 2014 to 2018. In corollary, non-HRE analysts follow firms with lesser exposure to prior epidemics.

We first examine the impact of analysts' prior epidemic experience on forecast accuracy by comparing the changes from the pre-COVID-19 period (the calendar year 2019) to the first two quarters of 2020 (during COVID-19) across HRE versus non-HRE analysts. The baseline results reveal that forecast accuracy for HRE analysts is significantly higher than for non-HRE analysts during COVID-19. Specifically, forecast errors significantly decrease by 0.6% and 0.15% for the "Recent" and "All" forecast samples, respectively. This finding suggests that analysts' prior epidemic experience leads to an enhanced ability to assess the uncertainty around the epidemic, thereby translating to higher forecast accuracy.

We next run cross-sectional tests along two dimensions to bolster the main inference. First, we examine the moderating role of the severity of the impact of COVID-19. We use three different measures to capture the same: (1) duration of lockdown in the respective U.S. states, (2) forecasts issued post declaration of COVID-19 as a pandemic by the World Health Organization (WHO) on 11th March 2020 and (3) firm-specific managerial sentiment toward COVID-19 captured by the negative tone in textual disclosures using Hassan *et al.* (2020) data. All three empirical measures recognize the severity of COVID-19. For example, U.S. states with longer lockdowns are likely to be experiencing a severe impact of COVID-19 that results in a more extended lockdown period.

Similarly, the recognition of COVID-19 as a pandemic by the WHO is likely to have happened after COVID-19 assumed a more severe form. Based on these four empirical measures, we document that the higher forecast accuracy of HRE analysts post-COVID-19 is concentrated in firms where the severity of the impact of COVID-19 is high. This finding further lends support to the argument that the prior experience of HRE analysts aids in resolving the uncertainty and forecasting more accurately when the experience becomes more relevant and essential, i.e. in instances when the severity of the disease is higher. Existing literature has fully documented that prior experience matters for analysts' forecast accuracy. We further examine the analysts' prior epidemic experience on forecast accuracy after three years of COVID-19. The results indicate that besides analyst industry experience, prior epidemic experience matters. Second, we implement a placebo test to see whether past epidemics experiences matter beyond pandemic time. Our results suggest that HRE analysts' forecast accuracy is significantly higher than that of non-HRE analysts outside COVID-19.

The last set of our cross-sectional analysis is based on the prevailing information environment of firms affected by COVID-19. To capture the information environment, we focus on the concentration of institutional ownership and the number of analysts following a particular firm (Franks, 2020; Yu, 2008). Firms with lower analyst-following and a lower percentage of institutional ownership are likely to have a poor information environment. Further, such firms are expected to have a higher degree of information asymmetry during COVID-19 because the baseline level of information quality of these firms is poorer to begin with. Thus, HRE analysts should exhibit higher forecast accuracy for these firms than non-HRE analysts. Our results confirm these conjectures. We find that HRE analysts have higher forecast accuracy than non-HRE analysts when they follow firms with lower institutional ownership and lower coverage by analysts.

The contributions of this study are of interest to both the academic community and policymakers. First, we add to the burgeoning literature on the role of capital market participants during COVID-19 by examining the analysts' forecast accuracy – the critical information agent in capital markets – during the pandemic (Landier & Thesmar, 2020). While the role of analysts' industry experience has been well explored in prior literature, evidence on the role of experience gained by analysts during prior epidemics is sparse. We add to this literature by documenting that prior epidemic experience plays a vital role in the accuracy of analysts during and after COVID-19.

Second, we contribute to the research on the systematic performance differences across analysts (Bradley *et al.*, 2017a; Kadan *et al.*, 2012). Specifically, the finding that the expertise acquired through an experience of following high-risk firms in the past enhances analysts' performance during the pandemic sheds light on a critical differentiator that partially explains the systematic difference in performance across analysts. Bradley *et al.* (2017a, b) document that industry experience and knowledge are the most crucial factors related to analyst performance. We examine this line of argument at a more granular level (analyst-firm level) using the setting of an exogenous shock, i.e. COVID-19, and show that industry experience alone does not help improve forecast accuracy during a pandemic – prior experience of tracking firms during epidemics adds incremental accuracy to analysts' forecasts during pandemics such as COVID-19.

Finally, our findings should prompt macroeconomic policymakers at the national level, such as the central banks of countries, to include past epidemic experiences as a key determinant when forecasting the economic outlook and making policy-related decisions. Moreover, practitioners and advisory firms can improve the earnings prediction models by placing more weight on pandemic-adjusted forecasts made by analysts with past epidemic experience.

The remainder of the paper is organized as follows. Section 2 provides the background and development of the hypotheses. Section 3 provides the research design, followed by empirical findings, and the last section concludes the paper.

2. Institutional setting and research question

2.1 COVID-19

The coronavirus disease, or COVID-19, is an outcome of the spread of the novel coronavirus, starting from the city of Wuhan in China. The spread started towards the end of 2019 and gradually became a global epidemic by March 2020 when the WHO declared COVID-19 a pandemic. The effect of COVID-19 is still being felt worldwide as we write this paper, with millions of infections and deaths wreaking havoc on humanity and causing massive damage to the economies of almost all nations (Nicola *et al.*, 2020). During COVID-19, several industries, such as agriculture, petroleum, manufacturing, education, etc., faced grave uncertainty about their prospects. The retail industry, which is the backbone of several economies, witnessed a sharp decline in consumer spending (Bose, Shams, Ali, & Mihret, 2022). The uncertainty induced by COVID-19 stems from the fact that there is no viable prediction of when the effects of COVID-19 are likely to subside. Even though vaccines have been rolled out around the globe, the effects of COVID-19 will likely continue to affect most nations in the foreseeable future.

A growing stream of research in Finance examines the impact of COVID-19 on financial markets. For example, Ashraf (2020) documents an adverse stock market reaction to a growing number of positive COVID-19 cases across 64 countries. Zhang *et al.* (2020) find that the volatility of global financial markets increases substantially during COVID-19. Giglio *et al.* (2021) show an increase in investor pessimism about future growth during the stock market crash during February-March 2020. Several other studies examine the impact of COVID-19 on various aspects of financial markets, such as debt markets (Zaremba *et al.*, 2022), derivative markets (Jackwerth, 2020), etc. In sum, the research thus far on the impact of COVID-19 reaches the consensus that COVID-19 induced unparalleled uncertainty in global financial markets.

2.2 Research question

To motivate our study, we draw upon the analyst literature that documents the role of experience in shaping analysts' forecasts. Prior research documents that analysts gain expertise in select industries allowing them to achieve economies of scale in information production, and such expertise is valued by the investors (Kadan *et al.*, 2012). Industry experience also allows analysts to play the role of external monitors more effectively (Bradley *et al.*, 2017a, b). Survey evidence supports these findings and shows that institutional investors and analysts consider industry experience a key attribute for success (Brown, Call, Clement, & Sharp, 2015). Given the importance of industry expertise in investors' view, prior literature examines whether industry expertise leads to tangible benefits. For example, Bradley *et al.* (2017a) document that prior experience in specific industries allows analysts to forecast more accurately. Taken together, it can be inferred from prior literature that industry experience plays a crucial role in analysts' forecasting accurately both within and across industries.

Building upon this line of argument, we propose that prior experience in tracking firms during epidemics should allow analysts to forecast more accurately when a global health crisis such as COVID-19 induces uncertainty across most industries. At first glance, one could argue that prior industry experience will likely aid the analyst in forecasting accurately when the industry faces a global health crisis. However, we argue that because firms within the same industry have varying health-related risks (Hassan *et al.*, 2020), industry experience alone is unlikely to mitigate the adverse effect of a health crisis on analysts' ability to forecast accurately. If analysts have experience tracking firms during epidemics, they can leverage this experience and forecast more accurately during COVID-19.

On the other hand, several factors could negate any benefits arising from the prior epidemic experience of analysts. First, if analysts have tracked epidemics such as H1N1, Ebola, etc., the experience might be less relevant during COVID-19 because of the different natures of epidemics. Second, analysts work harder during uncertain times (Loh and Stulz, 2018), which could substitute for the difference in experience between HRE and non-HRE analysts. Hence, the difference between the forecast accuracy of HRE and non-HRE analysts could be insignificant during COVID-19. Third, analysts' spillover literature suggests inexperienced analysts tend to follow experienced analysts and attempt to forecast closer to the consensus forecasts during uncertainty (Cen *et al.*, 2020). Therefore, during COVID-19, non-HRE analysts could mimic HRE analysts leading to an insignificant difference in their forecast accuracy. Because the impact of analysts' prior epidemic experience on forecast accuracy is unclear ex-ante, we examine this question empirically.

3. Research design and sample selection

3.1 Research design

To examine the role of prior epidemic experience on analyst forecast accuracy, we run the following Ordinary Least Squares (OLS) specification:

$$FE_{i,j,t} = \alpha_{i,j} + \beta_1 HRE_{i,j,t} + \beta_2 COVID_{i,j,t} + \beta_3 COVID_{i,j,t}\, x\, HRE_i + \beta_4 Controls_{i,j,t} + \varepsilon \quad (1)$$

Where, $FE_{i,j,t}$ is the forecast error computed by an analyst i for firm j at time t, scaled by the prior quarter stock price $(t-1)$ and then multiplied by 100. The variable $COVID_{i,j,t}$ takes a value of 1 from January 2020 to June 2020 and zero otherwise. The variable HRE_i takes a value of 1 for HRE analysts and zero otherwise. The firm-specific exposure is computed using a textual approach (Hassan *et al.*, 2020). We control for firm characteristics and the cross-sectional determinants of forecast errors such as firm size (SIZE), book-to-market ratio (BTM), financial leverage (LEV), and free cash flows (FCF), the number of analysts issuing a forecast (ANALYST_ISSUING), the years of experience of the analyst in following a given firm (DURATION), earnings surprise indicator (BAD NEWS), financial constraints (KZINDEX), and industry experience (IND_EXPERIENCE). We also include firm and analyst fixed effects $(\alpha_{i,j})$ to control for the time-invariant unobserved variables along those dimensions and cluster the standard errors at firm and forecast period end date for robust inference. Variable definitions are provided in Appendix. The coefficient for the interaction term (β_3) reports the incremental change in forecast accuracy for HRE analysts during the COVID-19 period compared to non-HRE analysts. If prior experience in following firms during a health crisis is positively associated with forecast accuracy, we expect β_3 to be negative and significant. On the other hand, if prior experience in following firms during a health crisis is irrelevant to forecast accuracy, then β_3 should be insignificant.

3.2 Sample and variable measurement

We start by collecting quarterly data relating to analysts' earnings forecasts from the I/B/E/S database from 1st January 2019 to 31st March 2023. Our primary variable of interest is analyst forecast error, computed as the absolute value of the difference between actual earnings and forecasted earnings scaled by the recent quarterly stock price [3]. This forecast data is merged with Compustat quarterly data for financial variables, such as firm leverage, size, book-to-market ratio, FCF, Kaplan and Zingale's index (Kaplan & Zingales, 1997), and total investment expenditures. Additionally, analyst-specific variables computed are duration (i.e., the number of years since the analyst first followed the firm), analyst coverage, and an indicator variable for the bad news.

We use two different samples for the study - "Recent" and "All". The "All" sample consists of every forecast issued by an analyst for each firm-forecast period end date (including revisions), while the "Recent" sample retains only the most recent forecast issued by an analyst prior to the announcement of actual value for each firm-forecast period end date. We filter to retain only quarterly forecasts and merge with Compustat to compute our control variables. We further filter to retain forecasts issued by HRE or non-HRE analysts and merge them with pandemic-specific variables used in cross-sections. This results in a final sample of 194,980 analyst forecasts for the "All" sample. A similar procedure is followed for the "Recent" sample, except only the recent forecast by an analyst is retained for each forecast period, resulting in a final sample of 136,836 analyst forecasts for the "Recent" sample. All variables are winsorized at 1 and 99% levels [4]. Table 1 presents the descriptive statistics of key regression variables for both the "Recent" and "All" samples.

We define HRE analysts as analysts with prior forecasting experience for firms with higher exposure to health-related risk. We use the textual measure provided by Hassan *et al.* (2020) to quantify firm exposure to past epidemics - SARS, H1N1, Ebola, and Zika. The measure captures a firm's exposure risk to these epidemics by counting the number of times the managers discuss words [5] related to these epidemics in the quarterly earnings conference calls, scaled by the total number of words in the earnings call transcript. We average firms' exposure between the years 2014 and 2018. Firms in the top quartile are regarded as firms with 'higher' exposure to epidemics, and analysts following such firms are identified as HRE analysts [6].

4. Results

4.1 Univariate test

We begin the analysis with a univariate test before conducting a formal regression analysis. If the forecast performance of HRE analysts and non-HRE analysts differs during COVID-19, we expect to capture this empirically in a univariate test. To conduct this test, we identify the pre-COVID-19 period as forecasts issued between 1st January 2019 and 31st December 2019, based on forecast period end dates. The COVID-19 period is for all forecast period end dates from 1st January 2020. The univariate results are presented in Table 2 across Panel A ("Recent" sample) and Panel B ("All" sample). For the "Recent" sample, the results indicate that the average forecast error of non-HRE analysts increases from 0.389% in the pre-COVID period to 0.615% in the

Variable	Mean	Std. Dev	p25	Median	p75
Panel A: Summary statistics – "recent" sample					
Dependent Variable					
FE	0.561	1.312	0.058	0.171	0.486
Independent Variables					
HRE	0.244	0.429	0	0	0
COVID	0.697	0.459	0	1	1
Control Variables					
SIZE	8.774	1.935	7.484	8.747	10.023
ANALYSTS_ISSUING	12.418	7.131	7	11	17
DURATION	5.383	4.222	2	4	8
BAD_NEWS	0.242	0.428	0	0	0
LEV	0.326	0.205	0.164	0.321	0.462
FCF	−0.037	0.155	−0.108	−.029	0.041
KZINDEX	−1752.203	32090.798	−3271.525	−466.521	107.875
INVESTMENT	0.043	0.060	0.007	0.023	0.054
BTM	0.428	0.396	0.146	0.300	0.589
IND_EXPERIENCE	8.273	5.389	4	7	11
Cross-Sectional Test Variables					
HIGH INTENSITY	0.200	0.400	0	0	0
PANDEMIC	0.665	0.472	0	1	1
NEGATIVE SENTIMENT	0.243	0.429	0	0	0
CONCENTRATION	0.217	0.412	0	0	0
ANALYST_FOLLOWING	0.172	0.378	0	0	0
Panel B: Summary statistics – "all" sample					
Dependent Variable					
FE	0.598	1.290	0.063	0.188	0.543
Independent Variables					
HRE	0.237	0.426	0	0	0
COVID	0.713	0.452	0	1	1
Control Variables					
SIZE	9.014	1.959	7.683	8.934	10.287
ANALYSTS_ISSUING	12.757	6.943	7	12	17
DURATION	5.531	4.286	2	4	8
BAD_NEWS	0.254	0.435	0	0	1
LEV	0.325	0.206	0.161	0.320	0.462
FCF	−0.034	0.160	−0.107	−0.027	0.044
KZINDEX	1502.226	41885.506	−3185.478	−402.188	315.653
INVESTMENT	0.041	0.058	0.006	0.021	0.052
BTM	0.448	0.406	0.154	0.318	0.630
IND_EXPERIENCE	8.352	5.399	4	7	12
Cross-Sectional Test Variables					
HIGH INTENSITY	0.208	0.406	0	0	0
PANDEMIC	0.658	0.474	0	1	1
NEGATIVE SENTIMENT	0.239	0.427	0	0	0
CONCENTRATION	0.219	0.413	0	0	0
ANALYST_FOLLOWING	0.202	0.402	0	0	0

Note(s): This table presents summary statistics for the sample firms. The sample spans the period 2019-2023. Panel A reports summary statistics for the "Recent" sample (N = 136,836), and Panel B reports summary statistics for the "All" sample (N = 194,980). All continuous variables are winsorized at the 1 percent and 99 percent levels. All variables are described in Appendix
Source(s): Table 1 by authors

Table 1.
Descriptive statistics

	Pre-COVID-19 period (1)	Forecast error COVID-19 period (2)	Differential effect (2) – (1)
Panel A: "Recent" sample			
N	41,411	95,425	
non-HRE analysts	0.389	0.615	0.226***
HRE analysts	0.541	0.631	0.090
Diff-in-diff			*−0.136****

	Pre-COVID-19 period	Forecast error COVID-19 period	Differential effect (2) – (1)
Panel B: "All" sample			
N	55,880	139,100	
non-HRE analysts	0.394	0.675	0.281***
HRE analysts	0.498	0.649	0.151
Diff-in-diff			*−0.131****

Note(s): This table provides the univariate results for HRE and non-HRE analysts across two periods, i.e., pre-COVID-19 and during COVID-19. Panel A reports the results for the "Recent" sample (N = 136,836), and Panel B reports the results for the "All" sample (N = 194,980)
Source(s): Table 2 by authors

Table 2.
Univariate results

COVID period. At the same time, there is no significant increase in the average forecast error of HRE analysts from the pre-COVID period to the COVID period. The overall differential effect (Diff-in-Diff) is −0.136 and statistically significant at the 1% level. The findings are qualitatively similar in Panel B for the "All" sample. Overall, the univariate test results support our prediction that analysts' prior epidemic experience allows them to forecast better during COVID-19.

4.2 Main results

We begin a formal empirical analysis by estimating the model in equation (1) and present the results in Table 3 for both "Recent" and "All" samples. Columns (1) and (2) document the results in the absence of any control variables for "Recent" and "All" samples, respectively, while the results in column (3) and column (4) document results after including control variables, for "Recent" and "All" samples respectively. In column (1) and column (2), the coefficient β_2 is +0.236 and + 0.291, statistically significant at the 1% level. This suggests that, on average, forecast errors for non-HRE analysts increase during COVID-19 compared to pre-COVID-19. Further, in the same columns, the coefficient of interest β_3 is −0.136 and −0.133, respectively, and statistically significant at the 1% level. This suggests that the increase in forecast errors for HRE analysts is significantly smaller than that of non-HRE analysts. For instance, in column (1), the forecast errors for HRE analysts increase by 0.1 ($\beta_1 + \beta_2$), compared to 0.158 for non-HRE analysts. Thus, the findings in Table 3 indicate that while COVID-19 adversely impacts the forecast accuracy for all analysts, the impact is muted for HRE analysts, suggesting that the prior health-related experience of HRE analysts mitigates the adverse impact of COVID-19 on forecast accuracy.

4.3 Cross-sectional tests

To bolster the main findings, we conduct cross-sectional analyses to identify how the strength of the association between prior experience of tracking firms during health crises and forecast errors varies in the cross-section of firms. To conduct the cross-sectional analyses, we use the following model:

Dependent: FE	(1) Recent	(2) All	(3) Recent	(4) All
HRE	0.103***	0.111***	0.106***	0.115***
	(4.58)	(5.48)	(5.21)	(6.34)
COVID	0.236***	0.291***	0.281***	0.335***
	(23.02)	(26.97)	(28.08)	(32.20)
HRE * COVID	−0.136***	−0.133***	−0.152***	−0.160***
	(−6.28)	(−6.49)	(−7.45)	(−8.40)
SIZE			−0.125***	−0.104***
			(−21.52)	(−18.94)
ANALYSTS_ISSUING			0.000	−0.002**
			(0.21)	(−2.35)
DURATION			0.001	0.000
			(0.64)	(0.23)
BAD_NEWS			0.204***	0.244***
			(17.56)	(21.73)
LEV			0.816***	0.848***
			(22.27)	(23.89)
FCF			−0.268***	−0.380***
			(−5.28)	(−7.88)
KZINDEX			−0.000***	−0.000
			(−3.58)	(−0.46)
INVESTMENT			−0.400***	−0.465***
			(−6.05)	(−7.52)
BTM			0.986***	0.952***
			(35.89)	(37.72)
IND_EXPERIENCE			−0.005***	−0.005***
			(−3.98)	(−4.12)
Constant	0.374***	0.475***	0.103	0.068
	(3.91)	(3.27)	(1.02)	(0.45)
Observations	136,836	194,980	136,836	194,980
R-squared	0.0497	0.0594	0.1626	0.1778
Firm and Analyst FE	Y	Y	Y	Y

Note(s): This table reports the results from estimating equation (1) using an OLS specification. Columns (1) and (3) report results for the "Recent" sample (N = 136,836), and columns (2) and (4) report results for the "All" sample (N = 194,980). Robust *t*-stats based on standard errors clustered at firm-forecast period end date level are included in parentheses. Two-tailed *p*-values are indicated: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All variables are described in Appendix
Source(s): Table 3 by authors

Table 3. Main result

$$FE_{i,j,t} = \alpha_{i,j} + \beta_1 * COVID_{i,j,t} + \beta_2 * COVID_{i,j,t} * HRE_i + \beta_3 Feature_{i,j,t} + \beta_4 * HRE_i * Feature_{i,j,t} + \beta_5 * COVID_{i,j,t} * Feature_{i,j,t} + \beta_6 * COVID_{i,j,t} * HRE_i * Feature_{i,j,t} + \beta_7 * Controls_{i,j,t} + \varepsilon \quad (2)$$

In equation (2), the dummy variable *Feature* refers to the cross-sectional variable being examined in the tests. We interact Feature with HRE analyst and COVID-19 variables for each cross-sectional test to capture the differential effect of prior experience based on the cross-sectional characteristics. The coefficient for the triple interaction term (β_6) captures the incremental effect of HRE analysts' impact on forecast accuracy across the respective features during the COVID-19 period. All the control variables are the same as in equation (1).

4.3.1 Degree of COVID-19 impact. The main finding in this paper suggests that analysts' prior experience of following firms during health crises aids them in reducing forecast errors induced by the uncertainty due to COVID-19. If this is true, then the prior experience of analysts should be more helpful in reducing the forecast error for firms where the severity of the impact of COVID-19 is high. Thus, we predict the extent of association of analysts' prior health experience with their forecast errors should be stronger for firms that faced a higher degree of impact from COVID-19. We use four different empirical proxies to estimate the impact of COVID-19 on firms. The first measure of the extent to which a firm is affected by COVID-19 is based on the duration of state-level lockdowns in the U.S. These lockdowns were government-imposed to contain the pandemic, and a longer duration of these lockdowns in certain states suggests that the severity of COVID-19 was higher in these states based on the assessment done by the government. In addition, longer lockdowns are likely to impact the business of firms operating in these states to a greater extent, thus making it more difficult for analysts to forecast the earnings of these firms. Sparse literature on COVID-19 supports this argument and uses lockdowns as a proxy for the impact of COVID-19 (Bose *et al.*, 2022). Under such circumstances, analysts' prior experience in dealing with uncertainties induced by epidemics will likely help them forecast more accurately. Thus, the duration of the first lockdown phase is a reasonable proxy for the impact of COVID-19. Accordingly, we estimate equation (2) with the variable *Feature* denoting 1(0) for states with lockdown duration in the top (other) quartile and report the results in columns (1) and (2) of Table 4. Consistent with the main finding, the coefficient β_2 continues to be negative and significant, suggesting that forecast errors for analysts with health crisis experience are smaller during COVID-19. The coefficient of interest (β_6) is also negative and significant in both samples, suggesting that in states where the duration of lockdown is longer, prior experience of analysts enables them to forecast more accurately compared to those states where the lockdown duration was below the median value in the sample.

The second measure of the extent to which a firm is affected by COVID-19 is based on the date of the issuance of forecasts by analysts. We posit that the forecasts issued post the declaration of COVID-19 as a pandemic by the WHO are likely to be less accurate as the overall uncertainty increases. This is supported by recent literature that shows that informational uncertainty increased after 11th March 2020, when the WHO declared COVID-19 a pandemic (Baig & Chen, 2021). Thus, the declaration of COVID-19 as a pandemic is an acceptable proxy for the impact of COVID-19 on informational uncertainty. Accordingly, we estimate equation (2) with the variable *Feature* denoting 1 for the period after 11th March 2020 and 0 otherwise. We report the results in columns (1) and (2) of Table 5. Consistent with the main finding, the coefficient β_3 continues to be negative and significant, suggesting that forecast errors for analysts with health crisis experience are smaller during COVID-19. The coefficient of interest (β_6) is also negative and significant at 1% in both columns, suggesting that after COVID-19 was declared a pandemic, prior experience of analysts enables them to forecast more accurately compared to the period before the declaration of COVID-19 as a pandemic.

The third and final measure of COVID-19's impact on a firm is based on the managerial sentiment toward COVID-19. We use the sentiment measure proposed by Hassan *et al.* (2020), wherein they identify the discussion related to COVID-19 (as discussed earlier) and then capture the proportion of positive/negative words in this discussing using the dictionary provided by Loughran & Mcdonald (2011). We posit that a negative tone/sentiment towards the pandemic indicates a detrimental impact on such firms. When managers adopt a negative sentiment during the earnings call, it suggests that the firm is likely to be affected significantly in the future. Thus, the prospects of the firm are marked by a higher degree of uncertainty, and forecasting by analysts is likely to be impacted adversely. However, if analysts have prior experience of tracking firms during similar epidemics, the adverse impact

Dependent: FE	HIGH INTENSITY Recent (1)	All (2)
HRE	0.095***	0.104***
	(3.92)	(4.81)
COVID	0.248***	0.294***
	(21.17)	(23.55)
HRE * COVID	−0.128***	−0.130***
	(−5.26)	(−5.71)
Feature	−0.104***	−0.103***
	(−5.44)	(−5.92)
HRE * Feature	0.025	0.013
	(0.62)	(0.41)
COVID * Feature	0.108***	0.124***
	(5.11)	(5.70)
HRE * COVID * Feature	−0.072**	−0.082***
	(−1.68)	(−2.06)
Control Variables	Y	Y
Observations	136,836	194,980
R-squared	0.1630	0.1782
Firm and Analyst FE	Y	Y

Note(s): This table reports the results from estimating equation (2) using OLS. Column (1) reports results for the "Recent" sample (N = 136,836), and column (2) reports results for the "All" sample (N = 194,980). Robust *t*-stats clustered at firm level are included in parentheses. The variable *Feature* denotes HIGH INTENSITY. Two-tailed *p*-values are indicated: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All variables are described in Appendix
Source(s): Table 4 by authors

Table 4.
Duration of LockDown

Dependent: FE	PANDEMIC Recent (1)	All (2)
HRE	0.106***	0.115***
	(5.24)	(6.36)
COVID	0.144***	0.261***
	(6.96)	(16.68)
HRE * COVID	−0.079**	−0.075**
	(−2.05)	(−2.46)
Feature	0.067	0.091
	(0.14)	(0.19)
HRE * Feature	1.648***	1.748***
	(3.51)	(3.66)
COVID * Feature	0.078	−0.010
	(0.17)	(−0.02)
HRE * COVID * Feature	−1.725***	−1.839***
	(−3.66)	(−3.85)
Control Variables	Y	Y
Observations	136,836	194,980
R-squared	0.1629	0.1779
Firm and Analyst FE	Y	Y

Note(s): This table reports the results from estimating equation (2) using OLS. Column (1) reports results for the "Recent" sample (N = 136,836), and column (2) reports results for the "All" sample (N = 194,980). Robust *t*-stats clustered at firm level are included in parentheses. The variable *Feature* denotes PANDEMIC. Two-tailed *p*-values are indicated: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All variables are described in Appendix
Source(s): Table 5 by authors

Table 5.
Declaration of pandemic

on forecast accuracy is likely to be mitigated by this experience. Consequently, we code the 'Feature' variable as 1(0) for firms with COVID-19-specific sentiment in the top (other) quartile. Using this definition of Feature, we estimate equation (2) and document the results in Table 6. The coefficient β_6 is significantly negative in both columns, suggesting that analysts' prior health experience aids them in forecasting more accurately for firms where managers signal negative sentiments related to COVID-19 to the market participants. Taken together, this set of cross-sectional tests strongly implies that HRE analysts' forecast accuracy is higher when firms are affected relatively more by COVID-19, thus bolstering the paper's main finding.

4.3.2 Ex-ante information environment. The next set of cross-sectional tests examines the prevailing information environment of firms. We posit that firms with relatively higher ex-ante information asymmetry will have higher uncertainty to begin with. Compounded with the uncertainty induced by COVID-19, analysts' forecast accuracy would be more adversely affected for such firms, which is likely to increase the importance of the prior epidemic experience of analysts. Therefore, we posit that the forecast accuracy of HRE analysts will be higher during COVID-19 for firms with a poor information environment before the advent of COVID-19. The first proxy of the information environment is institutional investor concentration sourced from 13-F filings. A firm's lower number of institutional investors leads to higher information asymmetry (Franks, 2020). Using institutional investor concentration to capture the ownership by these investors, we code the 'Feature' as 1(0) for firms with institutional investor concentration in the top (other) quartile. A higher concentration value denotes a lower percentage of ownership by institutional investors. Using this definition of *Feature*, we estimate equation (2) and document the results in Table 7.

	NEGATIVE SENTIMENT	
	Recent	All
Dependent: FE	(1)	(2)
HRE	0.085***	0.092***
	(3.52)	(4.29)
COVID	0.259***	0.317***
	(24.65)	(27.78)
HRE * COVID	−0.113***	−0.119***
	(−4.71)	(−5.30)
Feature	−0.002	−0.009
	(−0.10)	(−0.45)
HRE * Feature	0.080*	0.086**
	(1.81)	(2.27)
COVID * Featurem	0.102***	0.079***
	(3.94)	(3.14)
HRE * COVID * Feature	−0.151***	−0.153***
	(−3.17)	(−3.55)
Control Variables	Y	Y
Observations	136,836	194,980
R-squared	0.1632	0.1781
Firm and Analyst FE	Y	Y

Note(s): This table reports the results from estimating equation (2) using OLS. Column (1) reports results for the "Recent" sample (N = 136,836), and column (2) reports results for the "All" sample (N = 194,980). Robust *t*-stats clustered at firm level are included in parentheses. The variable *Feature* denotes NEGATIVE SENTIMENT. Two-tailed *p*-values are indicated: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All variables are described in Appendix
Source(s): Table 6 by authors

Table 6.
Negative managerial sentiment towards COVID-19

Dependent: FE	Concentration Recent (1)	All (2)
HRE	0.047***	0.079***
	(2.83)	(4.88)
COVID	0.262***	0.315***
	(30.47)	(33.43)
HRE * COVID	−0.079***	−0.110***
	(−4.72)	(−6.31)
Feature	0.238***	0.216***
	(8.12)	(7.99)
HRE* Feature	0.255***	0.158***
	(4.01)	(3.01)
COVID * Feature	0.065*	0.066*
	(1.86)	(1.95)
HRE * COVID * Feature	−0.312***	−0.227***
	(−4.61)	(−3.87)
Control Variables	Y	Y
Observations	136,836	194,980
R-squared	0.1696	0.1834
Firm and Analyst FE	Y	Y

Note(s): This table reports the results from estimating equation (2) using OLS. Column (1) reports results for the "Recent" sample (N = 136,836), and column (2) reports results for the "All" sample (N = 194,980). Robust t-stats clustered at firm level are included in parentheses. The variable *Feature* denotes Concentration. Two-tailed p-values are indicated: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All variables are described in Appendix
Source(s): Table 7 by authors

Table 7. Institutional investor concentration

The coefficient β_6 is −0.312 (−0.227) in column 1 (column 2) of Table 7, suggesting that when the institutional ownership is low, HRE analysts outperform non-HRE analysts in forecasting more accurately during COVID-19.

The second proxy for the information environment is the analyst coverage for a firm. Since lower analyst coverage relates to lower information availability (Yu, 2008), we expect analysts' experience to matter more for such firms. Consequently, we code 'Feature' as 1(0) when the analyst-following is in the lowest (other) quartile. Using this definition of *Feature*, we estimate equation (2) and document the results in Table 8. The coefficient β_6 is −0.315 (−0.228) in column 1 (column 2) of Table 8, suggesting that HRE analysts outperform non-HRE analysts in forecasting more accurately during COVID-19 when the analyst-following is low. Together, these findings shed light on the role of analysts' prior epidemic experience in improving their forecast accuracy during COVID-19 when the firms' information environment is not transparent.

5. Conclusion

The uncertainty induced by the COVID-19 pandemic increases uncertainty in global financial markets. Under such circumstances, analysts' role as information intermediaries gains even more importance. This leads to an important question: What determines analysts' forecast accuracy during the COVID-19 pandemic? Building upon prior literature on the role of analyst experience in shaping analysts' forecasts, we examine whether experience in tracking firms exposed to prior epidemics allows analysts to forecast more accurately during COVID-19. We find that analysts with experience in forecasting for firms with high exposure to epidemics (H1N1, Zika, Ebola, SARS) exhibit higher accuracy than analysts without such experience.

Dependent: FE	ANALYST_FOLLOWING Recent (1)	All (2)
HRE	0.056***	0.077***
	(3.14)	(4.52)
COVID	0.272***	0.333***
	(28.84)	(31.52)
HRE * COVID	−0.089***	−0.107***
	(−4.73)	(−5.64)
Feature	0.148***	0.087***
	(4.45)	(3.04)
HRE * Feature	0.244***	0.167***
	(3.54)	(3.16)
COVID * Feature	0.044	−0.001
	(1.14)	(−0.05)
HRE * COVID * Feature	−0.315***	−0.228***
	(−4.32)	(−4.01)
Control Variables	Y	Y
Observations	136,836	194,980
R-squared	0.1648	0.1785
Firm and Analyst FE	Y	Y

Note(s): This table reports the results from estimating equation (2) using OLS. Column (1) reports results for the "Recent" sample (N = 136,836), and column (2) reports results for the "All" sample (N = 194,980). Robust t-stats clustered at firm level are included in parentheses. The variable *Feature* denotes ANALYST_FOLLOWING. Two-tailed p-values are indicated: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All variables are described in Appendix
Source(s): Table 8 by authors

Table 8.
Analyst following

Further, this effect of experience on forecast accuracy is more pronounced while forecasting for firms with higher exposure to the risk of COVID-19 and for firms with a poor ex-ante informational environment.

We contribute to several strands of literature, and our findings should interest both academicians and practitioners. First, we add to the burgeoning literature on the role of capital market participants during COVID-19 by examining the analysts' forecast accuracy – the key information agent in capital markets – during the pandemic (Landier & Thesmar, 2020). While the role of analysts' industry experience has been well explored in prior literature, evidence on the role of experience gained by analysts during prior epidemics is sparse. We add to this literature by documenting that prior epidemic experience assists analysts in improving their forecast accuracy during COVID-19. Second, we contribute to the research on systematic performance differences across analysts (Bradley *et al.*, 2017a; Kadan *et al.*, 2012). Specifically, the finding that the expertise developed through an experience of following high-risk firms in the past enhances analysts' performance during the pandemic sheds light on a key differentiator that partially explains the systematic difference in performance across analysts. Third, Bradley *et al.* (2017a, b) document evidence that industry experience and knowledge are the most crucial factors related to analyst performance. We examine this line of argument at a more granular level (analyst-firm level) using the setting of an exogenous shock, i.e. COVID-19, and show that industry experience alone does not help improve forecast accuracy during a pandemic – prior experience of tracking firms during epidemics adds incremental accuracy to analysts' forecasts during pandemics such as COVID-19.

These findings underline the role of analysts in mitigating the ambiguity and uncertainty in the information environment around the COVID-19 period. Consequently, these findings make a novel contribution to the literature on sell-side analysts' forecast accuracy by providing evidence on the usefulness of prior epidemics' experience during the COVID-19 pandemic. Our findings imply that during the uncertain times induced by COVID-19, investors could choose to trust and rely upon the forecasts and reports generated by HRE analysts. Based on our findings, HRE analysts utilize their prior experience of tracking firms exposed to epidemics and forecast more accurately. Thus, HRE analysts' reports are likely to benefit investors more than those generated by non-HRE analysts.

Our study opens avenues for future research. First, while our paper examines the forecast accuracy of HRE analysts in the initial months of COVID-19, future research could investigate how the forecast accuracy of HRE analysts compares to that of non-HRE analysts over the subsequent months. It would be important to document whether the forecast accuracy of HRE analysts and non-HRE analysts converges as COVID-19 continues or whether HRE analysts can maintain superiority in forecast accuracy. Second, in the last two years, the U.S. government has provided financial aid and assistance to several industries. Future research could examine if the government's policy measures moderate the ability of HRE analysts to forecast more accurately.

Notes

1. https://hbr.org/2022/03/business-forecasts-are-reliably-wrong-yet-still-valuable
2. We cluster all specifications at Firm and Forecast period end date.
3. This measure has been used in several earlier studies, such as O'Brien (1988), Lys and Soo (1995) and Mikhail *et al.* (1997). We multiply the error measure with 100 for expositional ease.
4. We drop 1% outliers for each sample using DFBeta methodology by regressing forecast error on interaction variable of COVID and HRE: i.e. $FE_{i,j,t} = \alpha_{i,j} + \beta_1 COVID_{i,j,t}\, x\, HRE_i + \varepsilon_{i,j,t}$.
5. The words related to SARS are "sars", and "severe acute respiratory syndrome". Words related to Ebola and Zika are "ebola" and "zika" respectively, and words related to H1N1 are "hn", "swine flu", and "ahn".
6. We drop firms with zero average exposure to avoid selection bias.

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(The Appendix follows overleaf)

Appendix

Dependent Variable	
FE	Absolute Value of the difference between the actual earnings and the forecasted earnings, scaled by the stock price. This variable is multiplied by 100
Control Variables	
LEV	(*dlttq* + *dlcq*) Scaled by the lagged value of total assets
BTM	Common equity scaled by the market value of equity
FCF	(*oibdpq* - (*rectq* + *invtq* + *acoq* - *lcoq* -*apq*) - *capxy*)/*atq*
INVESTMENT	(*capxy* + *aqcy* + *xrdq*-*sppey*) scaled by lagged assets (Compustat items)
DURATION	Number of years since analyst first followed the firm
ANALYST_ISSUING	Number of analysts issuing a forecast for the firm by forecast period end date
SIZE	Natural log of total assets
BAD NEWS	Dummy Variable that takes a value of 1(0) when Surprise is negative (positive)
KZINDEX	Refer Kaplan & Zingales (1997)
IND_EXPERIENCE	Number of years an analyst has been following the same industry
Cross-Sectional Variables	
HIGH INTENSITY	Dummy variable equal to 1(0) for firms located in States of lockdown duration in the top (other) quartile
PANDEMIC	Dummy variable equal to 1(0) for forecasts issued after (before) 11th March 2020 (i.e., after the declaration of COVID-19 as a pandemic by the WHO)
HIGH CONCENTRATION	Dummy variable equal to 1(0) for firms with institutional investor concentration in the top (other) quartile
FEWER COVERAGE	Dummy variable equal to 1 for firms with analyst-following in the lowest quartile; 0 otherwise
Other Variables	
HRE	Dummy variable equal to 1(0) for analysts in the top (bottom) quartile of firms exposed to epidemic risks
COVID	Dummy variable equal to 1(0) if the forecast period end date is after (before) 1st January 2020

Source(s): Appendix by authors

Table A1.
Variable definitions

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