Hate Crimes and Analyst Forecast Behaviors Amidst the COVID-19 Pandemic†

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Abstract

We examine how forecast behaviors of East Asian financial analysts in the United States would change in the face of escalated crimes against Asians amid COVID-19. Using a DID approach, we find that compared with non-East-Asian analysts, East Asian analysts issue financial forecasts with lower boldness, higher pessimism, lower updating frequency, and less timely amidst the pandemic. The inferior forecast quality of East Asian financial analysts is associated with increased analyst herding, decreased consensus forecast accuracy, and lower post-earnings announcement abnormal returns. Our findings imply that racial animus and bias could distort forecast behaviors of analysts from ethnic minority backgrounds, resulting in reduced information efficiency and market valuation.

Keywords: COVID-19, Anti-Asian Hate Crime, Financial Analyst, Sell-Side Analyst, Forecast Boldness, Analyst Herding, Information Efficiency, Market Valuation

JEL Classification: G24; G30; G40; M14; I18

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"In the past, we would've just sucked it up and done what they needed to do. Now, our Asian American community here is speaking up, and they're going to their managers and saying, 'I'm not comfortable. Have you seen what's going on?'" [1]

- Alex Chi

Co-Chief Executive Office at Goldman Sachs BDC, Inc., May 21, 2021.

1 Introduction

The COVID-19 pandemic has had profound impacts on the US economy and society. One of the most severe social issues emerging amid the pandemic is the surge of Anti-Asian hate crimes (e.g., Gover, Harper, and Langton, 2020; Ziems, Soni, Ramakrishnan, Yang, and Kumar, 2021). During the first quarter of 2021, hate crimes against Asians increased by 164% compared with the first quarter of 2020 (Anglin, Cui, Gao, and Zhang, 2021). Several shocking hate crimes against Asians, such as the notorious 2021 Atlanta spa shootings, shrouded Asian communities under the shadow of fear, anxiety, and insecurity, which in turn adds another layer of negative emotions to the escalated tensions in the face of the evolving pandemic situation (Horse, Jeung, and Matriano, 2021). In the wake of the societal malevolence against Asian American communities and the potential impairments of the economy and society, the US administration and law authorities acted accordingly, and President Biden signed the COVID-19 Hate Crimes Act into law in May 2021.

Societal attention and legislative effort rendering the passage of the new Hate Crimes Act signifies the commitment to standing against hatred and racism at a national level. Still, the economic ramifications of the rampant hate crimes against Asians amidst COVID-19 and the resulting adverse effects on the psychological well-being and mental health of the Asian labor population in the US are less researched and understood rigorously. Indeed, the wavering

[1] https://www.cnbc.com/2021/05/21/why-asian-americans-on-wall-street-are-breaking-their-silence.html

and pessimistic sentiments immersing Asian American people stem not only from physical threats of violent crimes but also from their psychological perception of social discrimination (e.g., Horse, Jeung, and Matriano, 2021; Perng and Dhaliwal, 2022). Their disrupted professional behaviors and performance due to the shocks of heightened societal pressure stemming from the transmission of COVID-19 would likely undermine the full recovery of the US economy from the pandemic. In addition, empirical research is in its infancy on the influence of hate crimes in the extant finance literature, and little research has accumulated to date regarding the effects of racial animus on analyst forecast behaviors.

It is widely documented in the literature that financial analysts and their forecasts are important sources of information for investors (Kothari, So, and Verdi, 2016). Analysts provide forward-looking information innovation and analyze information already released to the market, thereby bridging the information gaps between public firms and investors, reducing overall information asymmetry, and enhancing market efficiency (Chang and Hsu, 2018). Their analyses and forecasts are important references for downgrading (Asquith, Mikhail, and Au, 2005). Firms followed by fewer financial analysts usually suffer more negative returns during the announcement period due to heightened information risk (e.g., D'Mello and Ferris, 2000). Hence, it is paramount for researchers and practitioners to understand the determinants of forecast behaviors of financial analysts.

Moreover, extensive literature illustrates the disruptive impact of personal life situations and catastrophic events such as terrorist attacks on financial analyst forecasts (e.g., Bourveau and Law, 2021; Cuculiza, Antoniou, Kumar, and Maligkris, 2021). Accordingly, the proliferation of hate crimes against Asian communities in the face of the pandemic shock introduces a significant amount of exogenous variation in the natural and historical trend of racial bias against Asian people (e.g. Wang, Gee, Bahiru, Yang, and Hsu 2020; Wu, Qian, and Wilkes 2021), creating a clean setting for empirically identifying the adverse impact on the professional performance of Asian financial analysts. In other words, focusing on financial analysts in the US, for whom quality demographic and forecast data are available, this study could essentially serve as a high-resolution snapshot of a short but very recent history amidst the pandemic, wherein the psychological and mental health of the Asian professionals are shattered by the rising malevolence and atrocities in their daily lives. Therefore, we aim to investigate the impact of Anti-Asian hate crimes on the forecast behaviors of Asian financial analysts in the face of the exogenous shock of COVID-19, during which the racial animus against Asian people was heightened, thereby filling the gap in the literature on analyst forecast behaviors and shedding light on the prolonged effects on the financial market in the aftermath of the pandemic.

To answer the research question, we conduct empirical analyses combining three sources. Specifically, we use the Thomson Reuters Institutional Brokers Estimate System (I/B/E/S), Hate Crime Tracker[2], and New York Times COVID-19 database for information about financial analysts and their forecasts, Anti-Asian hate crimes, and the evolving pandemic situation. Specifically, we collect the identity information of financial analysts through fuzzy matching censored names of analysts from I/B/E/S with full names of attendees from earnings conference call transcripts. We further tighten up the fuzzy matching results by a hybrid approach combining extensive manual data collection and web-scraping techniques in Python from various data sources, such as LinkedIn, Capital IQ, and Google, in search of supporting information (such as locations and face photos) about financial analysts. We use Family Search[3] to search analysts' last names and obtain information about countries of origin, and then manually check the classified East Asian analysts using other supporting information,

[2] Hate Crime Tracker (https://hatecrimetracker.1thing.org/) utilizes proprietary algorithms to constantly search for Anti-Asian hate crime incidents from various well-publicized and authoritative online sources. Hence, the data repository of the Anti-Asian Hate Crime Tracker website allows us to identify hate crime incidents against Asians, which are more likely to draw the attention of the society, and specialfly Asian communities.

[3] https://www.familysearch.org/en/surname?surname=

such as profile photos, to avoid mistaking racial classification. We successfully identify the race of 1,638 analysts, of which 152 (9.3%) analysts are from East Asian (including Southeast Asian) ethnic backgrounds.[4]

We utilize a standard difference-in-differences (DID) setting to examine the differences in forecast quality between East Asian analysts and non-East-Asian analysts before and after the exogenous shock of the COVID-19 pandemic. Consistent with the definition of the World Health Organization (WHO), we use March 2020 as the beginning of the pandemic period. Following Clarke and Subramanian (2006), our key variable of analyst forecast is relative boldness. Forecast boldness is considered one of the important indicators of analyst forecast quality in the sense that bold forecasts often incorporate more private information and insights from financial analysts than herding forecasts, thereby more effectively reducing information asymmetry and leveling the playground for investors (Clement and Tse, 2005). In addition, bolder analyst forecasts generate more trading for clients and thus more revenues for brokers (Irvine, 2004); hence, it is important to analyst's compensation and career prospects. Moreover, issuing bold forecasts is deeply related to behavioral factors such as self-assessed ability and confidence (Trueman, 1994), in which the proliferated Anti-Asian hate crimes could play an important role through the channels of deteriorating mental health and psychological well-being. As such, compared with other proxies for forecast quality, such as forecast accuracy, forecast boldness is a more astute metric that delineates how the forecast behaviors would alternate in the face of the pandemic shock and the resulting societal pressure and mental burden, thereby ameliorating concerns about confounding factors.

[4] We focus on East Asian (including Southeast Asian) analysts rather than the whole population of Asian analysts because the majority (over 97%) of victims of Asian hate crimes are East Asian and Southeast Asian. East Asian and Southeast Asian have different appearances (especially for their skin color of yellow) and are easy to be identified. Therefore, we do not include South Asian and West Asian analysts. However, our results still hold but much weaker if adding analysts with Indian last names while only 1.9% Anti-Asian hate crime incidents from January 2019 to September 2022 are targeted at people of Indian ethnicity. See Page 9 in the "Stop AAPI Hate National Report" from Horse, Jeung, and Matriano (2021) for details of the ethnic distribution of reported hate incidents.

We find that Asian financial analysts restrain from issuing bold forecasts relative to analysts of other ethnicities during the COVID-19 pandemic. In terms of economic significance, the forecast boldness of East Asian analysts has 2.1 percentage points drop relative to analysts of other ethnicities during the pandemic. Such a contraction in relative boldness is equivalent in magnitude to the decrease one may have in the face of definitive threat of employment termination, as documented in Clarke and Subramanian (2006), signifying its economic significance. The parallel trend test demonstrates that Asian financial analysts have comparative trends to financial analysts from other ethnic backgrounds for the variable of interest, relative boldness, suggesting that the key underlying assumption to the validity of difference-in-differences (DID) is readily in place. In addition, the DID results are robust to the placebo test where we substitute Hispanic analysts and female analysts for Asian analysts, illustrating the fact that the conduits for the empirical evidence are Asian-centric and are not intertwined with other confounding factors related to gender or ethnic minority biases.

Moreover, the empirical evidence also suggests that the forecasts of Asian financial analysts are more pessimistic, less frequently updated, and less timely amid the pandemic, suggesting inferior performance in terms of both quality and quantity. The additional findings further corroborate the results of the main variable of interest, forecast boldness, and taken together, the empirical evidence vividly depicts a wavering and hesitative profile of a typical East Asian analyst consumed by escalated societal bias and mental pressure stemming from the pandemic. Moreover, we find that there is no significant difference in terms of forecast accuracy between East Asian analysts and non-East Asian analysts. The seemingly surprising results suggest that the distorted forecast behaviors of Asian financial analysts do not necessarily dampen forecast accuracy. Facing the oppressive effects of the mental and psychological pressure on Asian people, Asian financial analysts are likely to modify their objective function by allocating more weight on taming their forecasts and going with the herds, and by giving up career development ambitions through investigating, analyzing and sharing unique information via bold forecasts. Nevertheless, this finding further demonstrates the contribution of this study, whereby focusing on the multifaceted metrics for suggesting East Asian analysts' deteriorating forecast quality is not driven by analysts' forecast ability change but mainly by mental and cognitive effects.

Furthermore, the remaining question is the primary cause for the findings. Are the findings more attributable to Anti-Asian hate crimes or Asian people's cautious attitude towards the pandemic? In other words, is it because the societal pressure of hate crimes against Asian people distorts Asian analysts forecast behavior, or is it because Asian people, influenced by their own culture, are more consumed by the uncertainty brought by the pandemic and are more pessimistic about the economic outlook amid the pandemic? Utilizing a staggered DID approach, we examine these two plausible mechanisms and identify the conduits for the main finding. Specifically, the empirical evidence suggests that the distorted forecast behaviors of Asian financial analysts are more attributable to the impact of escalated societal pressure caused by rising Anti-Asian hate crimes in the aftermath of pandemic waves rather than the rapidly evolving pandemic situation itself. This implies that our results are not driven by the cautious attitude towards pandemic diseases (such as wearing masks) arguably ingrained in East Asian culture or other relevant confounding factors such as an unusually pessimistic outlook on the economy amid the pandemic or reactional risk aversion to the uncertainty brought by the pandemic.

Finally, we find that the inferior forecast quality of Asian financial analysts is negatively associated with post-earnings announcement abnormal returns through reducing information efficiency. Notwithstanding the limited appearance of East Asian analysts, we find that the deteriorating performance of East Asian analysts spills over to their peers from other ethnicities, due to the strong herding among forecasts issued by analysts following the same firm. More analyst herding leads to lower analyst consensus forecast accuracy, which further reduces information efficiency. This indicates that financial analysts serve as a transmission mechanism through which the shock of the COVID-19 pandemic impacts information efficiency and valuation. Further, We find that the stock market react negatively to firms with East Asian financial analysts following around earnings announcement period. In terms of economic magnitude, we find that the abnormal return of a firm with East Asian analyst following is 2.5% lower in 10 days after earnings announcements during COVID.

Our study contributes to the literature in several dimensions. Our primary contribution is examining the determinants of analyst behaviors. The literature has shown that societal (e.g., school ties by Cohen, Frazzini, and Malloy (2010)), cultural (e.g., broker culture by Pacelli (2019), analyst cultural diversity by Merkley Michaely, and Pacelli (2020), and cultural bias by Pursiainen (2022)), behavioral and psychological (e.g., decision fatigue by Hirshleifer, Levi, Lourie, and Teoh (2019)), and environmental (e.g., air pollution by Dong, Fisman, Wang, and Xu (2021) and temperature by Addoum, Ng, and Ortiz-Bobe (2023)), gender (e.g., female analysts by Li, Peng, Shen, and Wong (2022)), and corporate disclosures (Chang, Ljungqvist, and Tseng 2023) factors affect analyst forecasts. Our paper demonstrates the adverse effects of deteriorating mental and psychological health caused by the rampant Anti-Asian hate crimes on forecast behaviors of Asian financial analysts amid COVID-19. To our best knowledge, our paper is the first paper to empirically identify the impact of racial animus on analyst forecast behavior. Merkley, Michaely, and Pacelli (2020) show that analyst racial diversity and diverse cultural origins have a positive impact on the quality of analyst output (i.e., the accuracy of consensus forecast). In addition to this finding, our paper indicates that societal malevolence and atrocities against a racial group have a negative spillover effect on the forecast accuracy of all the analysts through analyst herding, which is consistent with studies on peer effect and social learning among analysts (Kumar, Rantala, and Xu, 2022).

Our second contribution is to a growing literature examining disruptive life events on financial decisions (Bernile, Bhagwat, and Rau, 2017; Wang and Young, 2020). It has been shown that extreme adverse events, such as terrorist attacks, mass shootings, and deadly hurricanes, would adversely impact financial analysts' sentiment and forecasts (Bourveau and Law, 2021; Cuculiza et al., 2021). Our paper adds to the above stream of studies by demonstrating the negative effects of the COVID-19 pandemic on Asian analysts through escalated Anti-Asian hate crimes. Essentially, utilizing high frequency data on financial analysts, our research could be regarded as a high-resolution snapshot of a short but very recent history ranging from the shock of the pandemic to the passage of COVID-19 Hate Crimes Act, wherein Asian communities in the US are shrouded by fear and pressure stemming from racial animus against Asian people amid the pandemic.

Lastly, our paper contributes to the literature on the adverse effects of COVID-19. The pandemic has been shown to have negative impacts on people's mental health and psychological well-being through fear, anxiety, and discrimination (e.g., Almeida et al., 2020; Usher, Durkin, and Bhullar, 2020) and on rampant Anti-Asian hate crimes (e.g., Edara, 2020; Gover, Harper, and Langton, 2020; Lu and Sheng, 2022). Ben-Rephael et al. (2022) show that analysts with high pre-COVID traveling activities experience a significant reduction in forecast accuracy during the lockdown. Du (2023) and Li and Wang (2021) show that there are gender differences in analyst behaviors during COVID-19. Our paper demonstrates the impact of hate crimes and societal malevolence induced by COVID-19 on analyst behaviors, information efficiency, and stock returns.

2 Literature Review and Hypothesis Development

2.1 Financial Analyst Forecasts Boldness

Financial analysts play an important information discovery and interpretation role in the financial market. Analysts provide forward looking information innovation and analyze information already released to the market, thereby reducing information gaps between companies and investors, and enhancing the overall market efficiency through their forecasts and analyses (e.g., Chang and Hsu, 2018). Numerous studies have examined the multifaceted financial forecast behaviors, including forecast accuracy, stock recommendation, target price, forecast boldness, forecast speed, revision frequency, and market reaction, and their determinants, including analyst's skills, experience, agency conflicts, behavioral bias, and psychological well-being (Hilary and Menzly, 2006; Bourveau and Law, 2021; Hirshleifer, Bourie, Ruchti, and Truong, 2021).

There is a growing literature on the impact of exogenous and extremely adverse events such as terrorist attacks and mass shootings or disruptive personal life tragedies on analyst forecast behaviors through the channel of deteriorating mental health and psychological well-being. Specifically, it is found that financial analyst forecasts are subject to the influence of exogenous adverse events (Cuculiza et al., 2021), weather conditions (Bassi, Colacito, and Fulghieri, 2013), mood-introduced cognitive inaccuracy and distraction (Chang and Hsu, 2018) and decision fatigue caused by exogenous distraction (Hirshleifer et al., 2019).

In this paper, we focus on the psychological effects of hate crime during COVID on analyst's forecast behaviors. Specifically, we focus on analyst forecast boldness because it strongly relates to analysts' psychological factors than other forecast metrics. Forecast boldness is considered one of the important indicators of analyst forecast quality for two reasons. First, bold forecasts reflect either analysts' superior private information or unique insights in public information, thus providing fresh information and leveling the playground for investors (Clement and Tse, 2005). Therefore, a bolder forecast likely requires greater efforts from analysts. Second, a bolder forecast likely reflects greater confidence of analysts. Issuing bold forecasts is deeply related to behavioral factors such as self-assessed ability and confidence (Trueman, 1994). In addition, bolder analyst forecasts generate more trading for brokerage firms and thus more revenues (Irvine, 2004), which it is vital to analyst's compensation and career prospects.

Existing studies suggest that the market gives greater trust in bold forecasts because of the perceived rigor and prudence exercised by analysts in providing such opinions. Clement and Tse (2005) find that bold forecast revisions convey more new information and generate a stronger price impact than other forecast revisions. Dong, Liu, Lobo, and Ni (2022) find that analysts who issue excessively precise forecasts, such as ones with more digits after the decimal, tend to overweight their models more than experience. As such, they demonstrate higher levels of overconfidence, leading them to issue bolder forecasts. Keskek, Tse, and Tucker (2014) find that earlier forecasts contain more information discovery and thus have higher forecast boldness than later forecasts. Jame, Johnston, Markov, and Wolfe (2016) find that crowdsourcing forecasts on Estimize are bolder than and as accurate as IBES forecasts. Palmon, Sarath, and Xin (2020) classify extremely divergent recommendations as bold, and they find that bold recommendations have a strong impact on cumulative abnormal returns. Kumar et al. (2022) find that an analyst is more likely to issue bold forecasts when peers issued similar forecasts for other firms that the analyst is covering.

2.2 The COVID-19 Pandemic and Asian Hate Crimes

As the pandemic situation evolves, one rapidly developing literature focuses on the adverse effect of COVID-19 on the mental health of the public, especially the elderly, females, and Asians, through fear, anxiety, and discrimination. Specifically, COVID-19 introduced fear, panic, and discrimination, thereby deteriorating the mental health and psychological well-being of the public (Usher, Durkin, and Bhullar, 2020; Vindegaard and Benros, 2020). Especially, Wu, Qian, and Wilkes (2021) document that Asians face disproportionately severe mental disorders of COVID-19, which is in line with a growing stream of literature on the rampant Anti-Asian hate crimes amid the pandemic. In fact, the proliferation of COVID-19 cases and Asian hate crimes goes hand in hand in the US (e.g., Gover, Harper, and Langton, 2020), which is in part due to the early reports that indicated the potential linkage of Asian-style wet market to the transmission of COVID-19 and promoted labeling of Asian cultures as "other" and "backwards" (Perng and Dhaliwal, 2022). Racism in all forms, such as racial slurs, online bullying, and physical attacks, has become rampant and shrouded by COVID-19 (Edara, 2020). For example, the spread of COVID-19 has sparked racism and hate on social media targeted toward Asian communities (He et al., 2021).

2.3 Hypothesis development

Building upon the previous literature on exogenous shock and financial analyst forecasts, recent studies examine the impact of the COVID-19 shock on analyst forecasts from various perspectives. For example, female analysts' forecast accuracy declined more than male analysts amid the COVID-19 pandemic due to limited attention and disproportionate distractions that female analysts have to deal with while working from home (Li and Wang, 2021; Du, 2023). In a similar vein, Anglin et al. (2021) document that the rapidly evolving pandemic situations lead to forecast inaccuracy and dispersion. Focusing on the firms operating in areas of severe pandemic, Gao, Wen, and Yu (2021) demonstrate that the forecast dispersion of analysts increases for those firms exposed to unexpected inter-area mobility restrictions.

In addition, an emerging stream of literature documents that the proliferated hate crimes amid the COVID-19 pandemic result in a hostile environment of racial animus, thereby deteriorating the mental health of Asians (Anderson, Crost, and Rees, 2020; Wang, Gee, Bahiru, Yang, and Hsu, 2020; Wu, Qian, and Wilkes, 2021; Lantz and Wenger, 2022). As such, utilizing the clean empirical setting created by the sheer rise of social bias and malevolence against Asian people in the face of the exogenous shock of the COVID-19 pandemic, this study proposes to examine the influence of race and ethnicity, an crucial demographic trait of financial analysts, on their forecast behaviors amid the pandemic, whereby illustrating that racial animus is an important determinant of analyst forecasts.

Moreover, racial hate crime is different from other advese social or natural events, such as terrorist attacks (Cuculiza et al., 2021), hurricanes (Gallagher and Hartley, 2017), and police shootings (Anglin et al., 2021), in the sense that it not only incurs uncertainty and spreads fear like other adverse events, but also disturbs the targeted racial group with perceived discrimination, resulting in prolonged mental burdens. Specifically, hate crimes and societal malevolence can lead to many mental health consequences and psychological trauma to targeted communities, including anxiety, distress, depression, feelings of vulnerability, sleep disturbances, self-blame, diminished self-efficacy, and sense of disempowerment (Hein and Scharer, 2013). In addition, it has been documented in criminology literature that people exposed to violent and criminal threats express pessimistic risk perception and risk-averse choices because of the cognitive effect of the lack of safety and trust (Lerner and Keltner, 2001). Therefore, in the face of the rising Anti-Asian hate crimes amid the COVID-19 pandemic, Asian financial analysts are likely to alternate their objective function by focusing on taming and herding their forecasts and by restraining career development ambitions through investigating, analyzing, and sharing unique information via bold forecasts. As such, our main hypothesis can be stated as follows.

Hypothesis 1: The rising Anti-Asian hate crime amid COVID-19 pandemic deteriorates the forecast boldness of East Asian financial analysts.

Based on the above main proposition, we further predict that the deteriorating performance of Asian financial analysts driven by the pandemic-caused hate crimes would lead to a higher level of pessimism, decreased updating frequency, and delayed timeliness. Despite that forecast accuracy and forecast boldness are complementary properties to measure analysts' forecast quality (Hilary and Hsu (2013), it is unclear whether the psychological trauma and societal pressure caused by hate crimes would have a directional effect on analysts' forecast, in that risk-averse Asian financial analysts, with a pessimistic outlook on personal life and career prospect, may strive to uphold forecast accuracy at the cost of limiting bold forecasts.

We further examine the economic ramifications of the deteriorating forecast boldness of Asian financial analysts. As documented in Kumar et al. (2022), social learning among analysts would lead to herding behaviors. Accordingly, the distorted forecast behaviors of Asian financial analysts shall have negative spillover effect on other analysts, thereby dampening the forecast quality of all the financial analysts and the overall market informational efficiency. As such, our second hypothesis can be stated as follows.

Hypothesis 2: Deteriorating forecast boldness of East Asian financial analysts leads to more herding behaviors among analysts covering the same firm and lower consensus forecast accuracy during COVID-19.

Moreover, it is widely documented in the literature that financial analysts play an important role in information discovery and interpretation in the financial market (e.g., Clarke and Subramanian, 2006; Bradshaw, 2011; Chang and Hsu, 2018). As such, distorted analyst forecast behaviors might induce reduced information environment, biases in the trading decisions of investors and undermine market efficiency (Jiang, Kumar, and Law, 2016; Hirshleifer et al., 2019). Hence, we expect that the financial market would react negatively to the distorted behaviors of East Asian analysts in the face of heightened uncertainty and risk of information asymmetry. As such, our third hypothesis can be stated as follows.

Hypothesis 3: Deteriorating forecast boldness East Asian financial analysts is associated with lower abnormal returns after earnings announcements during COVID-19.

3 Data, Sample and Univariate Analysis

3.1 Data Sources and Sample Construction

We construct the sample for the empirical study by first obtaining analyst and forecast data from the Thomson Reuters Institutional Brokers Estimate System (I/B/E/S) starting from March 2019, one year before the shock of the COVID-19 pandemic officially ascertained by the WHO, through November 2021, roughly keeping symmetrical sample periods before and after the pandemic shock. Specifically, we use the data file of I/B/E/S detail history (unadjusted) for quarterly analyst forecasts as measured by earnings per share (EPS) for the U.S. companies. We only select analyst forecasts whose forecast period indicator (FPI) from I/B/E/S is either 6 or 7, namely, forecasts only for the current and the next fiscal quarter to ensure the timeliness of the forecast-related measures.[5] Furthermore, we adjust all estimates and earnings announcement dates to the closest preceding trading date in CRSP to match the corresponding adjustment factors. Then, the estimates are adjusted by CRSP adjustment factors to ensure the same per-share basis as the reported EPS.

Notice that I/B/E/S only provides information about analysts' last names, first initials and the brokerage firm code in lieu of full names. To collect identity information about analysts, we use fuzzy matching, a textual analysis approach, in Python to link possible full names based on attendee information from the past ten years of conference call transcripts (2010-2019) and Google search. We then further narrow down the potential full names and identify the most possible one for each analyst by manually collecting information from Capita IQ with the help of web scrapping. Next, we use the analyst's full name to determine its gender and ethnicity using Python packages (Selenium). Utilizing a hybrid approach of manual collection and web-scrapping, we further supply the sample with additional information about the analysts' living

[5] Our results are robust if we restrict FPI to equal 6 only.

and employment locations from sources such as Capital IQ, LinkedIn and Google search. We remove financial analysts who are based outside the U.S. from the sample. Notice that to ameliorate the confounding effects of employment risk, we only keep analysts who issue forecasts both before and after the pandemic shock. In addition, we also remove earning announcements without Asian analysts following or having only Asian analysts following.

To identify analysts' ethnicities, we use Family Search and manual checks. First, we search analysts' last names to get the top 3 countries of origin, and we classify a last name as potential East Asian if at least one of the top 3 countries of origin is located in East Asian and Southeast Asia. Then, we manually check classified potential East Asian analysts by using analysts' additional information (such as first names, education, and face photos) to exclude any misclassified East Asian analysts. For example, James Lee (at Mizuho Securities, his AMASKCD ID in I/B/E/S is 79306) could be both American and Korean. We manually check the name using Google Search and identify him as an East Asian analyst using his face photo.[6] In an effort to determine the ethnicity of each analyst, we search for their photos on platforms such as TipRanks, LinkedIn, or Google pages. By analyzing the appearance of the analysts in these photos, we aim to discern whether they have East Asian origins. This process also involves including analysts whose names do not suggest Asian origin but whose photos indicate East Asian ethnicity.

The above procedure results in a sample at firm-analyst-forecast level consisting of 1,638 analysts, out of which 152 (9.3%) are East Asian analysts. Table 1 shows the breakdown of our sample selection process and the sample of unique analysts identified. Table 2 presents the geographical distribution of analysts in our final sample. The majority of financial analysts in our sample are based in New York (61.0%) and California (8.4%). In comparison, 71.7% of

[6] https://www.tipranks.com/experts/analysts/james-lee

East Asian analysts are located in New York and 10.5% are in California, which are larger than the whole sample as most East Asian population in the U.S. live in New York and California.

We obtain data on Anti-Asian hate crimes from the website of Anti-Asian Hate Crime Tracker[7] created by Li Ma, founder of 1 Thing Inc., a non-profit organization against racism.[8] The proprietary algorithm of the website constantly searches for Anti-Asian hate crime incidents from various publicly available online sources, and then collect and aggregate the data to develop the open-source repository. Each data point of a hate crime incident is accompanied by a brief excerpt of the report and the corresponding hyperlink to the original source, typically a well-publicized news report. As such, utilizing the data repository of the Anti-Asian Hate Crime Tracker website, we can identify hate crime incidents against Asians, which are of severer nature, more likely to draw the attention of the society and Asian communities, and of greater and prolonged negative impact on the psychological well-being of Asian financial analysts.

As demonstrated in the time-series graph of Figure 1, the number of Anti-Asian hate crimes hikes roughly from March 2020 when the global pandemic of COVID-19 kicks off. Several waves in the aftermath of the pandemic shock include the Atlanta spa mass shootings and the following Stop Asian Hate protest in March 2021, and the number of incidents falls as the passage of the COVID-19 Hate Crimes Act in May 2021. As total, there were 576 Anti-Asian hate crime incidents reported in our sample period. Its accompanying graph, Figure 2, presents the geographical distribution of hate crime incidents across the US, depicting the landscape of aggregated hate crimes by state. Apparently, the hate crime incidents against Asians primarily largely accumulate in New York, New England region, and California, and

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[7] https://hatecrimetracker.1thing.org/
[8] The results are qualitatively similar if we augument the sample with federal governanent crime records at https://crime-data-explorer.fr.cloud.gov/pages/explorer/crime/hate-crime

are highly correlated with the locations of Asian financial analysts, indicative of potential confounding effects driven by region-specific factors.

In addition to hate crimes, the evolving pandemic situation of COVID-19 might be in a potential mechanism which underlies the deteriorating psychological well-being of Asian financial analysts. Hence, we obtain daily reported cases of COVID-19 at the state level from New York Times COVID-19 database[9]. As such, the main sample of the study jointly utilizes three data sources: I/B/E/S, Hate Crime Tracker, and New York Times COVID-19 database for financial analysts, Anti-Asian hate crime and COVID-19 cases data, respectively. To formulate multivariate regression analyses, we further merge the sample with Compustat, CRSP, and Thomson Reuters Institutional (13F) holdings using Link Tables provided by Wharton Research Data Services (WRDS) to compute variables of firm fundamentals, stock market performance, and institutional ownership. The final consolidated sample for primary empirical analyses consists of 291,630 observations at the analyst-forecast level. Please refer to the Appendix for detailed variable definitions.

3.2 Key Variables Construction

Our main measure of analysts' forecast quality is relative forecast boldness (*Boldrel*). There are two main reasons for us to focus on *Boldrel*. Firstly, forecast boldness is considered one of the important indicators of analyst forecast quality because bold forecasts often incorporate more private information and insights from financial analysts than herding forecasts, thereby more effectively reducing information asymmetry and leveling the playground for investors (Clement and Tse, 2005). In fact, bold forecasts are more likely to be issued by historically accurate analysts, large brokerages analysts, frequent forecasters, and analysts with more general experience (Clement and Tse, 2005). Secondly, issuing bold

[9] https://github.com/nytimes/covid-19-data

forecasts or not is deeply related to behavioral factors such as reputation and career concerns (Scharfstein and Stein 1990), and self-assessed ability and confidence (Trueman, 1994), in which the shock of COVID-19 could play an important role through the channels of deteriorating mental health and psychological well-being.

Following the definition in (Clarke and Subramanian, 2006), we construct *Boldrel* as follows.

$$Bold_{i,j,t} = \left|F_{i,j,t} - F\right|,$$

in which $F_{i,j,t}$ denotes the forecast issued by analyst i for firm j at time t, and F is the mean forecast of all analysts other than analyst i who produce earnings per share (EPS) estimates for firm j in the period $[t-180, t]$. Next, we rank analyst forecast in descending order according to $Bold_{i,j,t}$, and then define the key metric of relative boldness as follows.

$$Boldrel_{i,j,t} = 100 - \frac{Rank_{bold_{i,j,t}} - 1}{n-1} \times 100$$

in which *n* is the analyst number. *Boldrel* ranges from zero to one hundred with higher value representing higher degree of forecast boldness relative to peer forecasts.

In addition, we also use several other measures. Following Cuculiza et al. (2021), we define $Pessimism_{i,j,t}$ as a dummy variable that takes the value of unity if the forecast for firm *j* by analyst i at time t is below past 180 days average. As an alternative measure of pessimism, we define $Rec\_Chg_{i,j,t}$ as a trinary variable equal to one if analyst *i* upgrades its previously outstanding forecast of firm j at time t, zero if there is no change, and negative one for downgrades (following Dehaan, Madsen, and Piotroski, 2017). As a proxy for forecast quantity, following Li and Wang (2021), $Frequency_{i,j,t}$ is defined as the number of forecasts issued by analyst i in month t for firm j. Following Kim, Lobo, and Song (2011), $Timeliness_{i,j,t}$ is defined as the difference between the number of days between the last earnings announcement date and analyst forecast date after that.

Our key explanatory variable, *East_Asian*, is a dummy variable that takes the value of unity for financial analysts of East Asian origins, and zero otherwise. *Post* is a dummy variable that takes the value of unity if an analyst's forecast is made within and after March 2020 (the beginning of the pandemic period) and zero otherwise.

3.3 Summary Statistics and Univariate Results

Following previous literature (e.g., Clement and Tse, 2005; Cuculiza et al., 2021; Li and Wang, 2021), we also incorporate into the model specification extensive control variables of firm fundamentals, analyst characteristics, and financial forecast properties to identify the relations among the focal variables of interest. Specifically, covariates of firm fundamentals include *Size*, *Marketcap*, *B/M*, *ROA*, *Earngrowth, Instown* and *R&D*, controlling for size by book and market value, valuation, profitability, earnings growth, institutional ownership, and R&D expenditures. Controlling for multifaceted characteristics of financial analysts such as their experience, brokerage firm and expertise, analyst variables *Experience*, *Top_Broker*, *ExpWithFirm,* and *Coveragefocus* are also incorporated in the empirical specification. Please refer to the Appendix for variable definitions.

The summary statistics of variables of interest, key explanatory variables, and other covariates are summarized in Table 3 at firm, analyst and forecast levels. Despite that the research data span over the most recent period of COVID-19 pandemic, the descriptive statistics are comparable to other studies in the literature (Cuculiza et al., 2021; Li and Wang, 2021). Compared with Non-East-Asian analysts, East-Asian analysts have higher forecast boldness (62.336 versus 60.398), less forecast pessimism (*Pessimism* 0.498 versus 0.504; *Rec_Chg* -0.025 versus -0.031), less frequently forecast update (12.495 versus 17.715), and lower degree of timeliness (-8.654 versus -8.072).

4 Empirical Results

4.1 Main Results of Difference in Differences

In the baseline difference-in-differences (DID) regression, we use $Boldrel_{i,j,t}$ as the dependent variable, which captures the analyst i's forecast boldness for firm *j* in quarter *t*. $\mathbb{X}_{i,j,t}$ and $\mathbb{Z}_{j,t}$ are vectors of firm level and analyst level covariates defined in Section 3, and γ represents a comprehensive set of granular fixed effects including fixed effects of analyst, firm and year-month levels.

$$
\begin{aligned}
Boldrel_{i,j,t} = \beta_0 + \beta_1 East_{Asian_i} + \beta_2 Post_t + \beta_3 East_{Asian_i} \times Post_t \\
+ \beta_4^T \mathbb{X}_{i,j,t} + \beta_4^T \mathbb{Z}_{j,t} + \gamma + \epsilon_{it}
\end{aligned}
\tag{1}
$$

Table 4 presents the findings in the DID setting as to whether East Asian financial analysts are restrained from issuing bold forecasts as measured by *Boldrel* in face of COVID-19 shock. Column (1) presents the results without control variables and fixed effects. Columns (2) - (5) demonstrate the empirical results controlling for varied sets of granular fixed effects at different levels such as analyst, firm, and year-month. In order to further isolate the effect of the COVID-19 pandemic on *Boldrel*, model specifications in Columns (2) - (5) also include extensive covariates controlling for firm, analyst, and financial forecast characteristics. The standard errors are clustered at the analyst-firm level.

Consistent with hypothesis 1, the estimated coefficients of the interaction term between binary variables of *Asian* and *Post* is negative and significant across all the model specifications from Columns (1)-(5). Moreover, the parameter estimates across the different model specifications are consistent in terms of both statistical significance and economic magnitude.

In Column (5), for example, the forecast boldness of East Asian analysts in post-COVID period is 1.307 lower than that of Non-East-Asian analysts in pre-COVID period, which is about 2.1 percentage points drop (1.307/62.336) from East-Asian analysts' average forecast boldness. Albeit seemingly limited by percentage, such a decrease is equivalent to what one may have under definitive threat of employment termination as documented in Clarke and Subramanian (2006), and thus is considered economically significant. In comparison, East Asian analysts have significantly higher forecast boldness than Non-East-Asian analysts in pre-COVID period. One counter-intuitive finding is that, as shown in Columns (1) through Columns (3), the coefficient of $Post$ is positive and significant at 1 percent, which seemingly contradicts the nature of the pandemic shock. However, considering the fact that the variable of interest, $Boldrel_{i,j,t}$, looks back over the past 6 month, the positively significant coefficient suggests that analysts, on average, are more prone to revise their forecasts away from the pre-pandemic consensus, consistent with escalated uncertainty facing analysts post-pandemic documented in the literature (e.g., Ben-Rephael et al. 2022).

The main empirical findings by DID are further corroborated by additional checks. Firstly, to mitigate the concerns about the confounding effects of other macro-level events, we conduct parallel trend test in event study setting and the results are summarized in Figure 3. Clearly, the parameter estimates of the focal interaction term turn negative for quarters since March 2020 according to WHO's definition of COVID-19 pandemic. The graph of parallel trend test suggests that it is the shock of COVID-19 that induces the decrease in *Boldrel* for East Asian financial analysts. The significant negative effect lasts about four quarters (until February 2021) with a decreasing trend. The duration of this effect is comparable to other disruptive events on analyst forecasts, such as a one-month period after terrorist attacks in Cuculiza et al. (2021) and a two-year period after deadly hurricanes in Bourveau and Law (2021). Because of the increasing social awareness and criticism of Asian hate crime, the occurrence of Stop Asian Hate movement starting March 2021, and the eventual passage of COVID-19 Hate Crimes Act in May 2021, the negative relation turns into insignificant. This indicates that the feelings of social support alleviates East Asian analysts' mental pressure and increases their self-efficacy and empowerment to issue bold forecasts.

In addition, we opt to examine the impact of the pandemic on forecast boldness of analysts from other demographic groups as the placebo test, thereby further corroborating the unique response of our focal group, Asian financial analysts, to the effects of COVID-19. Specifically, we look at Hispanic financial analysts, a well-recognized ethnic minority group in the financial services industry, and Female financial analysts in the knowledge that females are more likely to be victims of and emotionally influenced by violent crimes[10]. Specifically, we use database of Frequently Occurring Surnames 2010 Census to identify Hispanic ethnicity.[11] As shown in Table 5, the parameter estimates of the interaction term for both *Hispanic* and *Female* are all insignificant across all the model specifications from Columns (1) - (5), in support of the major argument of the study that the proliferated Anti-Asian hate crimes caused by the shock of COVID-19 pandemic expose Asian communities to heightened societal pressure, leading to deteriorating mental health and psychological well-being. In sum, the empirical evidence suggests that the conduits for the empirical evidence are Asian-centric and are not intertwined with confounding factors such as gender or ethnic minority biases in general.

4.2 Channel and Mechanism

Given the main findings, the focal challenge is to examine the most pervasive channel through which the exogenous shock of COVID-19 pandemic comes into effect. Essentially, we would like to examine whether Asian financial analysts indeed react to the societal pressure of heightened hate crimes or, in contrast, influenced by their own culture, Asian financial analysts are merely more consumed by the uncertainty brought by the pandemic and are more pessimistic about the economic outlook amid the pandemic. To unveil the main channel for the

[10] Over 60% of victims of crime incidents are female, according to Anti-Asian Crime Tracker by 1 Thing Inc.
[11] https://www.census.gov/topics/population/genealogy/data/2010surnames.html

documented effect of COVID-19 shock, we directly examine in a staggered DID setting whether or not the deteriorating Asian analyst forecast boldness are directly attributable to pandemic-caused hate crimes, which adversely affect mental health and psychological well-being of Asian financial analysts.

Accordingly, utilizing the Anti-Asian hate crime data of 576 incidents identified by solid and well-publicized news sources, we define one variable, *Crime*, to gauge the severity of hate crimes against Asian communities. Specifically, *Crime* is a continuous measure that accumulates the number of incidents identified in the location of the analyst within two weeks prior to her forecast.[12] As specified in a weighted staggered DID model below, crime shocks, $Crime_{i,t}$, represents the two analyst-time varying proxies for hate crime severity.

$$\begin{aligned} Boldrel_{i,j,t} = \beta_0 + \beta_1 East\_Asian_i + \beta_2 Crime_{i,t} \\ + \beta_3 East\_Asian_i \times Crime_{i,t} + \beta_4^T \mathbb{X}_{i,j,t} + \beta_4^T \mathbb{Z}_{j,t} + \gamma_{\sim} + \epsilon_{it} \end{aligned} \tag{2}$$

Table 6 shows the results. Consistent with the predictions of the study, the parameter estimates of the interaction terms between *Crime* and *Post* are negative and significant across all model specifications. Especially the staggered DID results by *Crime* are persistent across Columns (1) - (5), and are negatively significant, suggesting incidents of Anti-Asian hate crime could significantly undermine the forecast boldness of Asian financial analysts.

In comparison with the results of Anti-Asian hate crimes, it would be interesting to examine whether the progressive and evolving pandemic situation in its own right would lead to reduced *Boldrel* of Asian financial analysts. Hence, based on the state-level daily updated COVID-19 data from New York Times COVID-19 database, we create a dummy variable, *Pos_Cases*, which takes the value of unity if the growth rate of seven days moving average of

[12] We also use an alternative measure, *Crime_d*, which is a dummy variable that takes the value of unity if at least one incident is identified in the location of the analyst within two weeks prior to the forecast. The results are qualitatively similar with *Crime_c* and hence are not tabulated for brevity.

new cases is positive and zero otherwise. Clearly, *Pos_Cases* depicts the dynamics of the COVID-19 trend as to how fast the pandemic situation proliferates. As such, the below specification summarizes the regression model we utilize to examine the role of evolving pandemic situations in a staggered DID setting.

$$\begin{aligned} Boldrel_{i,j,t} = \beta_0 + \beta_1 East\_Asian_i + \beta_2 COVID\_Cases_{i,t} \\ + \beta_3 East\_Asian_i \times COVID\_Cases_{i,t} + \beta_4^T \mathbb{X}_{i,j,t} + \beta_4^T \mathbb{Z}_{j,t} + \gamma_\sim \\ + \epsilon_{it} \end{aligned} \quad (3)$$

As shown in Panel B of Table 6, the parameter estimates of the interaction terms between *Asian* and *Pos_Cases* are insignificant for all models in Columns (1) - (5), suggesting that the propensity of publishing bold forecasts is intact for Asian financial analysts during the period of increasingly proliferated COVID-19 cases. The seemingly surprising empirical finding demonstrates that the increasingly proliferated pandemic situation itself is not attributable to the deteriorating forecast behaviors of Asian financial analysts, which in turn suggests that our results are not driven by the cautious attitude towards pandemic diseases arguably ingrained in the East Asian culture. This finding is further corroborated by conducting a "horse race" between *Pos _Cases* and *Crime* in Panel C of Table 6.

Taken together, the empirical evidence suggests that the distorted forecast behaviors of Asian financial analysts are more attributable to the impact of escalated societal pressure caused by rising Anti-Asian hate crimes in the aftermath of pandemic waves rather than the rapidly evolving pandemic situation itself or other relevant confounding factors potentially stemming from the East Asian culture, such as an unusually pessimistic outlook on the economy amid the pandemic or reactional risk aversion to the uncertainty brought by the pandemic. It is the prolonged adverse effects on mental health and psychological well-being caused by pandemic-caused hate crimes that play a major role in deteriorating forecast quality rather than the rapidly evolving pandemic situation itself.

4.3 Additional Forecast Metrics

In addition to relative forecast boldness, the study also examines the multifaceted forecast behaviors of Asian financial analysts in the face of pandemic shock, including forecast pessimism (*Pessimism* and *Rec_Chg*), updating frequency (*Frequency),* forecast timeliness (*Timeliness*), and forecast accuracy (*Forecast Error*). Consistent with the main findings, we find that amid the COVID-19 pandemic, Asian financial analysts tend to issue more pessimistic forecasts, update their forecasts less frequently, and make less timely forecasts. In addition to statistical significance, it is noteworthy that the parameter estimates for the regression of $RecChg_{i,j,t}$ are also economically significant. For example, as demonstrated in Column (5) of Panel B in Table 7, the estimated coefficient of the interaction term is -0.025, representing 83.3% of the sample median level (-0.03). Taken together, the empirical evidence of the baseline result and the additional findings delineate a wavering, hesitative, and inactive profile of a typical East Asian analyst shrouded by escalated societal pressure amid the pandemic.

Panel E of Table 7 summarizes the parameter estimates for the regression of *Forecast Error*, which is the absolute difference between the forecasted EPS and the realized EPS scaled by the stock's price 12 months prior to the quarterly earnings announcement date. The results show that there is no significant difference in terms of forecast accuracy between East Asian analysts and non-East Asian analysts in the post-COVID period, suggesting that the deteriorating quality of East Asian analysts' forecast is not driven by their diminished professional expertise, but mainly driven by mental and cognitive effects. Under heightened mental and psychological pressure, Asian financial analysts are likely to tame their forecasts, herd with their peers, and restrain from issuing bold forecasts based on unique but less reliable information. The findings of less affected forecast ability also help to ameliorate the confounding effects of certain coinciding events during the pandemic, such as stay-at-home orders, which may disproportionately impact East Asian analysts because of cross-cultural differences in family responsibilities (such as how childcare is shared by Du (2023)).

4.4 Analyst Forecast, Herding, and Stock Valuation

The multifaceted empirical analyses have demonstrated that the exogenous shock of COVID-19 significantly mounts the level of racial animus against Asians, which in turn negatively affect the mental health and psychological well-being of Asian financial analyst, dampening their forecast behaviors. Hence, it would be important to further examine the economic ramifications of the deteriorating forecast behaviors of Asian financial analysts on stock valuation through its negative effects on information efficiency.

Utilizing a set of regressions at the firm-earnings announcement level (the same as the firm-quarter level) specified as follows, we demonstrate whether and how the decrease in forecast boldness of Asian financial analysts would dampen the forecast quality of all the financial analysts covering the same firm and the overall market informational efficiency.

Specifically, for each earnings announcement, the average level of Asian analyst forecast boldness is regressed against the average level of herding for all the analysts who follow the same firm as of the announcement. Following Clement and Tse (2005), we create a dummy variable that takes the value of one for a forecast that is between the analyst's own prior forecast and the consensus forecast, and zero otherwise. The consensus forecast is the median of past 180 days' forecasts by the time the forecast is announced. Then, our measure, *Herding*, is the average of the dummy variable at the firm-earnings announcement level.

Then, we examine analyst herding on consensus forecast accuracy. We use two measures to capture analysts' consensus forecast accuracy for a firm in a quarter.

Relative_Accuracy is the average of the difference between median forecast error of all analysts following a firm and the analyst's forecast error following the firm, scaled by standard deviation of forecast error of all analysts following the firm. *Absolute_Accuracy* is the difference of the mean EPS forecast and the real EPS, scaled by the real EPS.

In addition to regular control variables, we also include *Economic_Tie*, measured by the sector volume of US-China international trade in all the regressions, to control a firm's exposure to China and Asian analysts' high tendency to cover firms with economic tie to China,.[13] Our specifications are as follow.

$$Herding_{j,t} = \beta_0 + \beta_1 Boldrel\_Asian_{j,t} + \beta_4^T \mathbb{X}_{i,j,t} + \beta_4^T \mathbb{Z}_{j,t} + \gamma + \epsilon_{it}$$

$$Relative\_Accuracy_{j,t} = \beta_0 + \beta_1 Herding_{j,t} + \beta_4^T \mathbb{X}_{i,j,t} + \beta_4^T \mathbb{Z}_{j,t} + \gamma + \epsilon_{it} \quad (4)$$

$$Absolute\_Accuracy_{j,t} = \beta_0 + \beta_1 Herding_{j,t} + \beta_4^T \mathbb{X}_{i,j,t} + \beta_4^T \mathbb{Z}_{j,t} + \gamma + \epsilon_{it}$$

The empirical results of the above regressions are summarized in Table 8. Specifically in Columns (1) and (2), the estimated coefficients of $Boldrel\_Asian_{j,t}$ are negative and significant at 1%, illustrating a strong negative spillover effect of Asian financial analyst forecast boldness. Such a finding is consistent with the strong peer effect and social learning effect documented by Kumar, Rantala, and Xu (2022). Clearly, the deteriorating forecast boldness of Asian analysts caused by the heightened societal pressure and proliferated hate crimes amid the pandemic shall interact with forecast behaviors of other financial analysts, resulting in acute herding forecast activities. Moreover, as shown in Columns (3) - (6), analyst herding forecasts are significantly associated with lower consensus forecast accuracy as measured by $Relative\_Accuracy_{j,t}$ and $Absolute\_Accuracy_{j,t}$. In light of the widely documented focal role of financial analyst forecasts as an important source of information for

[13] We thank an anonymous reviewer from our previous submission for this suggestion.

financial market participants, the empirical evidence suggests that the deteriorating Asian financial analyst forecast behavior on market information efficiency.

Furthermore, in the wake of the inferior information environment and heightened uncertainty, it would be interesting to examine the market reactions to the displacement of the effective roles of financial analysts in leveling the playground and alleviating information asymmetry among investors (e.g. Bradshaw, 2011). Specifically, we use $Abnormal\_Return_{j,t}$, post-earnings announcement buy-and-hold abnormal returns over various windows (10 days, 15 days, and 30 days) benchmarked by Fama-French 3 factor model as the proxies for market reaction. To control for time-invariant firm unobservable (such as a firm's economic tie to China) and time trends, we include firm and year-month fixed effects. The firm-earnings announcement level (the same as the firm-quarter level) regression is then specified in Eq. (5) in a DID setting.

$$
\begin{aligned}
&Abnormal\_Return_{j,t} \\
&\qquad = \beta_0 + \beta_1 East_{Asian_i} + \beta_2 Post_t + \beta_3 East_{Asian_i} \times Post_t \qquad (5) \\
&\qquad + \ \beta_4^T \mathbb{X}_{i,j,t} + \beta_4^T \mathbb{Z}_{j,t} + \gamma_{\sim} + \epsilon_{it}
\end{aligned}
$$

As shown in Columns (1) - (4) in Table 9, the stock valuation is adversely affected by the interaction of COVID-19 shock and the presence of Asian financial analyst. The empirical results further verify that the deteriorating forecast quality of East Asian financial analysts result in inferior valuation caused by poor information environment, wherein uncertainty and risk of information asymmetry escalate.

4.5 Additional Robustness Checks

The results are also robust to a battery of robustness checks. In Table 10, we include additional and more granular fixed effects, such as earning announcement, city, and analyst-firm-fiscal quarter level fixed effects. The results are still in line with the main results despite the fact more covariates are dropped due to the severe multicollinearity problem of the saturated specification. In Table 11, we find that our findings are robust to alternative dependent variables and model specifications. We use three alternative measures. First, *Bold_pos*, is a dummy variable that takes the value of unity if an analyst's forecast is above both the analyst's own prior forecast and the consensus forecast immediately prior to the analyst's forecast, and zero otherwise. Second, *Bold_neg*, is a dummy variable that takes the value of unity if an analyst's forecast is below both the analyst's own prior forecast and the consensus forecast immediately prior to the analyst's forecast, and zero otherwise. Third, *Absolute Boldness*, is the absolute difference between an analyst's most recent earnings forecast for a firm in the first 2 months of a quarter, and the average consensus earnings forecast made by all other analysts covering the firm (following Chang, Ljungqvist, and Tseng, 2023). In Panels A and B, the opposite sign of the interaction term of *Bold_pos* to that of *Bold_neg* suggests that East Asian analysts further refrain from issuing positive bold forecasts, which in turn supports the main argument about the adverse impact of pandemic and societal pressure on mental and psychological well-being. In Panel C, we find that our results stand when using the absolute boldness measure, which mitigates the concern that the ranking approach to compute relative boldness may play a critical role in driving our results.

5 Conclusion

The exogenous shock of the COVID-19 pandemic sparks the rising Anti-Asian hate crimes, which in turn result in prolonged and scarfing adverse effects on the psychological well-being and mental health of the Asian population in the US. Utilizing the exogenous variation in the natural and historical trend of racial bias against Asian people caused by the pandemic, our study strives to examine the impact of the Anti-Asian hate crimes on the forecast behaviors of Asian financial analysts in a clean empirical setting, thereby filling the gap in the literature on analyst forecast behaviors and shedding light on the prolonged effects of hate crimes on the financial market in the aftermath of the pandemic.

We find that forecasts issued by Asian financial analysts are less bold compared with analysts of other ethnicities during the COVID-19 pandemic. The degree to which Asian financial analysts restrain from issuing bold forecasts is also economically significant, in the sense that the decrease is equivalent in size to one may have in the face of definitive threat of employment termination, as documented in Clarke and Subramanian (2006). Moreover, the empirical evidence on additional forecast behaviors suggests that the forecasts of Asian financial analysts are more pessimistic, less frequently updated, and less timely amid the pandemic, indicative of inferior performance in terms of both quality and quantity. Furthermore, the difference in terms of forecast accuracy between East Asian analysts and non-East Asian analysts is found to be insignificant, suggesting that Asian financial analysts, with pessimistic outlook on personal life and career prospect amid the pandemic, may strive to uphold forecast accuracy at the cost of limiting bold forecasts. Taken together, the additional findings on the multifaceted metrics depicts a wavering and hesitative profile of a typical East Asian analyst consumed by escalated societal bias and mental pressure stemming from the pandemic.

Further, we find that the inferior forecast quality of Asian financial analysts due to hate crime leads to more analyst herding behaviors and lower consensus forecast accuracy, and thereby is negatively associated with post-earnings announcement abnormal returns. Taken together, our results suggest that hate crimes have severe financial ramifications by reducing information discovery and market efficiency.

Despite based on rigorous empirical design, the findings and analyses of the study are subject to certain limitations, which sheds light into potential future research directions. Driven by the exogenous shock of the COVID-19 pandemic and less correlated with other endogenous variables to analyst forecast behaviors, Anti-Asian hate crime is found as the primary channel through which deteriorating financial analyst forecast behaviors materialize. However, the drivers of the deficient forecast quality of Asian financial analysts relative to analysts of other racial backgrounds must be multifaceted. Hence, it would be meaningful for future studies to identify the variety of channels that result in racial differences in financial analysts' distorted forecast behaviors during the pandemic, thereby contributing to the bigger literature on financial analyst behaviors and calling for more attention to racial equality in the profession and beyond.

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Appendix: Variable Definition

Variable	Description
Forecast & Analyst Characteristics	
Boldrel	The measure for forecast relative boldness follows the definition in Clarke and Subramanian (2006). Its value ranges from zero for the least bold analyst to a score of one hundred for the boldest analyst in given earning announcement.
Bold_neg	A dummy variable takes the value of unity if a forecast is below the analyst's own prior forecast and the consensus forecast immediately prior to the analyst's forecast.
Bold_pos	A dummy variable takes the value of unity if a forecast is above the analyst's own prior forecast and the consensus forecast immediately prior to the analyst's forecast. This measure follows Clement and Tse (2005) and Kumar, Rantala, and Xu (2022).
Pessimism	A dummy variable takes the value of unity if an analyst forecast is below past 180 days average forecast for a specific fiscal period of a firm. This measure follows Cuculiza et al. (2021).
Rec_Chg	A trinary variable takes the value of unity if the analyst upgrades her previously outstanding forecast for the firm's fiscal quarter, zero if there is no change, and negative one for downgrades. This measure follows Dehaan et al. (2017).
Updating Frequency	The forecast quantity measure counts the number of forecasts issued by an analyst for a specific fiscal quarter of a firm. This measure follows Li and Wang (2021).
Timeliness	The forecast timeliness measure is the opposite number of days between the last earnings announcement date and analyst forecast date after that. This measure follows Kim, Lobo, and Song (2011).
Forecast Error	The absolute difference between the forecasted EPS and the realized EPS, divided by the stock's price 12 months prior to the quarterly earnings announcement date. This measure follows Du (2023).
Forecast_Age	The forecast horizon measure is the natural logarithm of the number of days from analyst forecast date to the next earnings announcement date. This measure follows Clement (1999) and Hirshleifer et al. (2021).
PMAFE	The absolute difference between their forecast error and the median absolute error for firm j at time t, is divided by the median absolute error for firm j at time t. This measure follows Cuculiza et al. (2021).
Herding	A dummy variable that takes the value of one for a forecast that is between the analyst's own prior forecast and the consensus forecast, and zero otherwise. The consensus forecast is the median of past 180 days forecasts by the time the forecast is announced. This measure follows Clement and Tse (2005).
Relative_Accuracy	The average of the difference between median forecast error of all analysts following a firm and the analyst's forecast error following the firm, scaled by standard deviation of forecast error of all analysts following the firm. This measure follows Hirshleifer et al. (2019).
Absolute_Accuracy	The difference of the mean EPS forecast and the real EPS, scaled by the real EPS.
East_Asian	A dummy variable that takes the value of unity for financial analysts with East Asian origins, and zero otherwise.
Hispanic	A dummy variable that takes the value of unity for financial analysts with Hispanic origins, and zero otherwise.
Female	A dummy variable that takes the value of unity for female financial analysts, and zero otherwise.
Experience	The analyst experience measure counts the number of years since the analyst first appears in the I/B/E/S EPS forecast database.

ExpWithFirm	The analyst experience measure about a certain firm counts the number of years since an analyst first published a forecast for a specific company in the I/B/E/S EPS forecast database.
Coveragesize	The number of firms an analyst follows in a fiscal quarter.
Coveragefocus	The negative of the number of different industries classified by three-digit SIC codes that an analyst follows in the same fiscal quarter. It measures the degree to which an analyst focuses on certain fields.
Top_Broker	A dummy variable that takes the value of unity for analysts who are employed by top 10 largest brokerage firms.
Crime & COVID-19 New Cases	
Crime_c	The continuous Anti-Asian hate crime measure that accumulates the number of incidents identified in the location of the analyst within two weeks prior to her forecast.
Post	A dummy variable that takes the value of unity if an analyst's forecast is made within and after March 2020 (the beginning of the pandemic period), and zero otherwise.
New_Cases	The smoothed measure for the level of COVID-19 cases that take seven days moving average of daily new cases.
Neg_Cases	A dummy variable that takes the value of unity if the growth rate of 7 days moving average is negative and zero otherwise.
Pos_Cases	A dummy variable takes the value of unity if the growth rate of seven days moving average of new cases is positive and zero otherwise.
Firm Fundamentals	
Size	The book value of a firm's total assets.
MTOB	The market value of a firm's shareholder equity scaled by the book value of shareholder equity.
B/M	The market value of equity divided by stockholders' equity at the end of the most recent reported quarter prior to the analyst forecast date.
ROA	Earnings before extraordinary items divided by total assets at the end of the most recent reported quarter prior to the analyst forecast date.
R&D	Research and development expenditures divided by book value of assets at the beginning of the fiscal year.
Earngrowth	Change in earnings before extraordinary items scaled by the total assets of the firm between the most recent reported quarter prior to the analyst forecast date and that for the same fiscal quarter in the prior year.
Instown	Percentage of common shares outstanding held by institutional investors at the end of the most recent calendar quarter prior to the analyst forecast date.
Economic_Tie	The sector volume of US-China international trade (import plus export).
Market Reaction Metrics	
Abnormal_Return	Post-earnings announcement buy-and-hold abnormal returns over various windows (5 days, 10 days, 15 days, and 30 days) benchmarked by Fama-French three-factor model.
Boldrel_Asian	The ratio of average forecast boldness of Asian financial analysts over that of Non-Asian analysts for each earnings announcement.

Figure 1. Daily New Incidents of Anti-Asian Crime

The figure exhibits the time-series distribution of Anti-Asian hate crime incidents from January 2019 to September 2022. The yellow bar represents the daily number of new incidents. The figure is plotted based on the data source of Anti-Asian Hate Crime Tracker collected by 1 Thing Inc., a non-profit organization against racism.

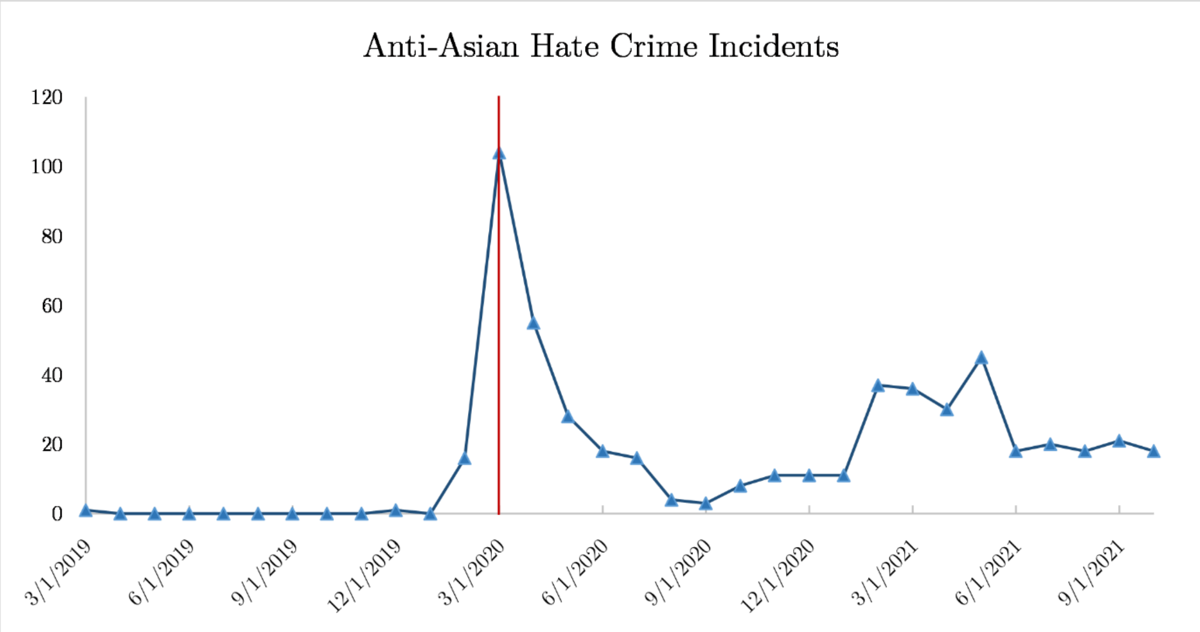

Figure 2. Anti-Asian Crime Geographical Distribution
The figure exhibits the geographical distribution of accumulated Anti-Asian hate crime incidents from January 2019 to September 2022. The degrees of brightness of yellow-shaded areas represent the levels of rampancy of Anti-Asian hate crime in that state. The figure is plotted based on the data source of Anti-Asian Hate Crime Tracker collected by 1 Thing Inc., a non-profit organization against racism.

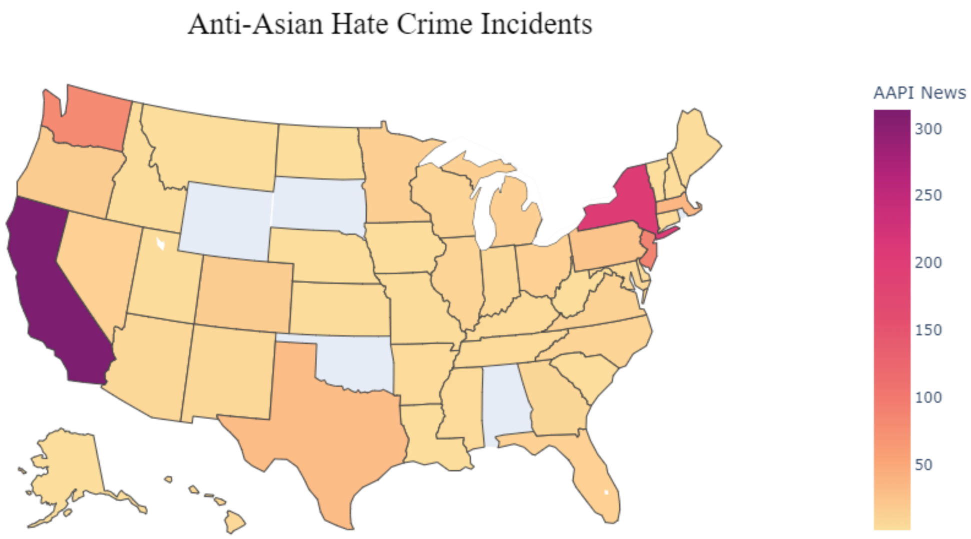

Figure 3. Parallel Trend Test by Event Study

The figure demonstrates the results of the parallel trend test in support of the main empirical evidence based DID approach. The parallel trend test is conducted in an event study setting wherein the key variable of interest, *Boldrel* is regressed against temporal dummies and their interaction with *East_Asian*, while controlling other covariates and fixed effects, the same as the specification in Column (5) of Table 4. The parameter estimates of the interaction terms are then plotted against the corresponding quarters relative to the event date, March 2020. Zero means December 2019 to February 2020. One means March 2020 to May 2020.

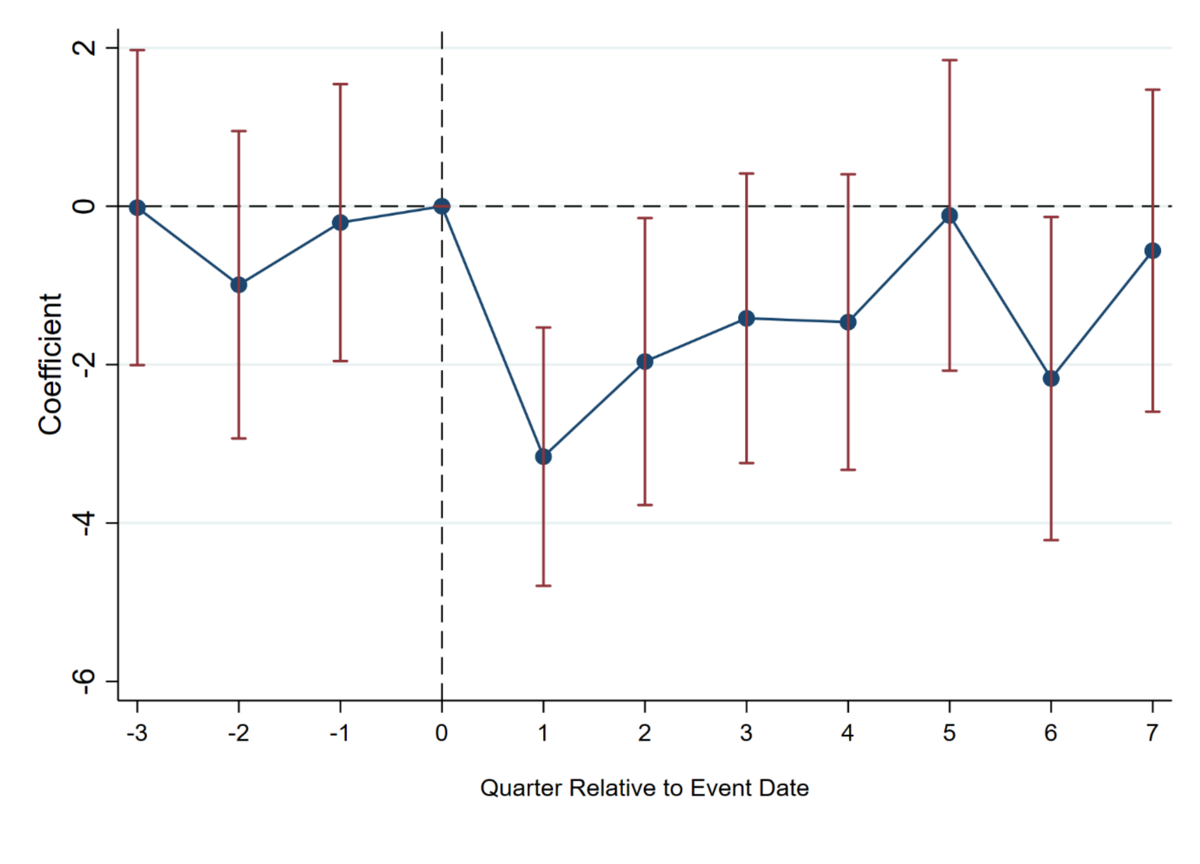

Table 1: Sample Construction Procedure

This table reports the detailed steps of constructing the main sample of financial analyst forecasts based on the data files from I/B/E/S. Forecasts# is the number of analyst forecasts at the firm-analyst-forecast level. Analysts# is the number of unique analysts (by I/B/E/S analyst ID, AMASKCD).

Sample Construction Procedure	Forecasts#	Analysts#
Select forecasts for the current and next fiscal quarter (FPI= 6 or 7) from March, 2019 through november, 2021 for US firm earning announcement	1205601	3896
Drop forecasts issued by analysts not clearly identified in I/B/E/S or the actual value of earnings announcement is missing	1047046	3449
Keep only analysts who issue forecasts both before and after Covid-19	792367	2263
Drop analysts whose full name and work location cannot be identified by manual data collection and analysts located outside the US	739787	1786
Drop earning announcement without Asian Analyst	308050	1645
Drop earning announcement only have Asian analyst.	305966	1638

Table 2: Geographical Distribution of Financial Analysts

This table reports the state-wide geographical distribution of financial analysts according to their work address. The states are sorted in descending order of the number of East Asian analysts who are located in the corresponding states in our sample. Analyst location data are collected from various sources such as S&P Captial IQ, LinkedIn, and Google Search.

State	Analysts#	Analyst%	East Asian Analysts#	East Asian Analysts%
NY	999	60.989	109	71.711
CA	138	8.425	16	10.526
CT	30	1.832	3	1.974
IL	73	4.457	3	1.974
MA	44	2.686	3	1.974
TX	42	2.564	3	1.974
FL	27	1.648	2	1.316
ME	5	0.305	2	1.316
NJ	15	0.916	2	1.316
OH	30	1.832	2	1.316
PA	13	0.794	2	1.316
MO	25	1.526	1	0.658
NC	2	0.122	1	0.658
OR	17	1.038	1	0.658
TN	18	1.099	1	0.658
WA	4	0.244	1	0.658
AL	2	0.122	0	0.000
AR	15	0.916	0	0.000
CO	9	0.549	0	0.000
DC	5	0.305	0	0.000
FI	3	0.183	0	0.000
GA	21	1.282	0	0.000
IA	2	0.122	0	0.000
KS	2	0.122	0	0.000
LA	10	0.611	0	0.000
MD	15	0.916	0	0.000
MN	40	2.442	0	0.000
MT	1	0.061	0	0.000
NM	1	0.061	0	0.000
NV	2	0.122	0	0.000
OK	1	0.061	0	0.000
TA	1	0.061	0	0.000
VA	24	1.465	0	0.000
WI	2	0.122	0	0.000
Sum	1638	100.000	152	100.000

Table 3: Summary statistics of the main sample

This table reports the summary statistics of the variables at different levels from the main sample based on the data file of I/B/E/S detail history, ranging from March 2019, one year before the shock of the COVID-19 pandemic, through November 2021. In addition to the full sample, the summary statistics are summarized for subsamples of East Asian and Non-East-Asian financial analysts. The sample selection and construction procedure is discussed in Section III. For detailed variable definitions are in Appendix.

	N	Mean	Median	p05	p95	Std. Dev.
Panel A: Full Sample						
			Firm Variables			
Size	13652	18.896	2.654	0.064	84.506	59.573
MTOB	13630	0.004	0.003	-0.001	0.021	0.107
Leverage	12577	0.000	0.001	-0.001	0.005	0.043
ROA	13650	-0.002	0.000	-0.006	0.001	0.095
Earngrowth	12832	-0.001	0.000	-0.001	0.002	0.102
Instown	13648	0.718	0.795	0.159	1.030	0.271
B/M	13630	0.474	0.295	-0.004	1.439	0.925
R&D	13657	0.028	0.004	0.000	0.117	0.058
			Forecast Variables			
Boldrel	293501	60.665	62.500	11.111	100.000	29.385
Bold_neg	305966	0.237	0.000	0.000	1.000	0.425
Bold_pos	305966	0.197	0.000	0.000	1.000	0.398
Pessimism	305966	0.503	1.000	0.000	1.000	0.500
Rec_Chg	305966	-0.030	0.000	-1.000	1.000	0.770
Frequency	34142	17.174	13.000	2.000	45.000	14.652
Timeliness	304297	-8.153	0.000	-91.000	58.000	37.454
Forecast_Age	305966	4.497	4.605	2.773	5.247	0.799
			Analyst Variables			
East_Asian	1638	0.093	0.000	0.000	1.000	0.290
All_Star	4445	0.071	0.000	0.000	1.000	0.257
Experience	4445	12.603	11.000	1.000	31.000	9.324
Top_Broker	1638	0.230	0.000	0.000	1.000	0.421
ExpWithFirm	4445	4.831	3.000	0.000	16.000	5.117
Coveragesize	34142	8.574	7.000	1.000	21.000	6.290
Coveragefocus	33988	4.421	4.000	1.000	10.000	2.985
Panel B: East Asian Analysts						
			Firm Variables			
Size	2581	11.026	0.857	0.030	54.991	43.188
MTOB	2576	0.005	0.003	0.000	0.018	0.069
Leverage	2434	0.001	0.000	0.000	0.004	0.022
ROA	2581	-0.007	0.000	-0.011	0.001	0.218
Earngrowth	2348	-0.004	0.000	-0.003	0.004	0.238
Instown	2579	0.640	0.696	0.079	1.009	0.307
B/M	2576	0.466	0.293	0.004	1.417	1.120
R&D	2581	0.044	0.021	0.000	0.159	0.066
			Forecast Variables			
Boldrel	40308	62.336	65.385	12.230	100.000	29.556
Bold_neg	42710	0.223	0.000	0.000	1.000	0.416

Bold_pos	42710	0.182	0.000	0.000	1.000	0.386
Pessimism	42710	0.498	0.000	0.000	1.000	0.500
Rec_Chg	42710	-0.025	0.000	-1.000	1.000	0.749
Frequency	3543	12.495	8.000	2.000	36.000	12.148
Timeliness	42302	-8.654	0.000	-91.000	53.000	37.152
Forecast_Age	42710	4.515	4.625	2.833	5.263	0.782
			Analyst Variables			
All_Star	427	0.026	0.000	0.000	0.000	0.159
Experience	427	8.253	5.000	0.000	25.000	8.045
Top_Broker	152	0.276	0.000	0.000	1.000	0.449
ExpWithFirm	427	3.703	2.000	0.000	13.000	4.934
Coveragesize	3543	6.298	4.000	1.000	17.000	5.361
Coveragefocus	3507	3.502	3.000	1.000	9.000	2.698
Panel C: Non-East Asian Analysts						
			Firm Variables			
Size	11071	20.731	3.310	0.082	93.879	62.641
MTOB	11054	0.003	0.003	-0.001	0.022	0.114
Leverage	10143	0.000	0.001	-0.001	0.006	0.046
ROA	11069	-0.001	0.000	-0.004	0.001	0.006
Earngrowth	10484	0.000	0.000	-0.001	0.002	0.006
Instown	11069	0.736	0.812	0.195	1.033	0.258
B/M	11054	0.476	0.295	-0.005	1.443	0.873
R&D	11076	0.025	0.001	0.000	0.106	0.055
			Forecast Variables			
Boldrel	253193	60.398	62.500	11.111	100.000	29.349
Bold_neg	263256	0.239	0.000	0.000	1.000	0.426
Bold_pos	263256	0.199	0.000	0.000	1.000	0.399
Pessimism	263256	0.504	1.000	0.000	1.000	0.500
Rec_Chg	263256	-0.031	0.000	-1.000	1.000	0.774
Frequency	30599	17.715	14.000	2.000	46.000	14.820
Timeliness	261995	-8.072	0.000	-91.000	60.000	37.502
Forecast_Age	263256	4.494	4.605	2.773	5.247	0.802
			Analyst Variables			
All_Star	4018	0.076	0.000	0.000	1.000	0.265
Experience	4018	13.065	12.000	1.000	32.000	9.332
Top_Broker	1486	0.225	0.000	0.000	1.000	0.418
ExpWithFirm	4018	4.951	3.000	0.000	16.000	5.122
Coveragesize	30599	8.838	8.000	1.000	21.000	6.337
Coveragefocus	30481	4.527	4.000	1.000	10.000	2.998

Table 4: Results of Difference in Differences for Relative Forecast Boldness

This table reports the empirical results of regressing the measure for relative forecast boldness, *Boldrel* against treatment dummy, *East_Asian* in a difference in differences (DID) setting. Following Clarke and Subramanian (2006), *Boldrel* measures forecast relative boldness that its value ranges from zero for the least bold analyst to a score of one hundred for the boldest analyst in a given earning announcement. *East_Asian* is a dummy variable that takes the value of unity for financial analysts of East Asian origin and zero otherwise. *Post* is a dummy variable that takes the value of unity if an analyst's forecast is made within and after March 2020 (the beginning of the pandemic period), and zero otherwise. Please refer to Appendix for other variable definitions. The sample is at analyst forecast level and ranges from March 2019 through November 2021. The results are estimated by linear regressions with different granular fixed effects, and standard errors are two-way clustered at the analyst-firm level. Standard errors are in the parentheses and *, **, *** denote levels of significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)
Post×East_Asian	-0.828*	-0.792*	-1.206***	-1.154***	-1.307***
	(0.45)	(0.47)	(0.45)	(0.45)	(0.44)
Post	2.249***	2.228***	3.475***		
	(0.16)	(0.17)	(0.24)		
East_Asian	2.479***	1.966***			
	(0.41)	(0.43)			
Forecast_Age		3.771***	3.612***	3.802***	3.859***
		(0.08)	(0.08)	(0.08)	(0.08)
All_Star		0.282	0.976	1.045	1.317**
		(0.29)	(0.68)	(0.68)	(0.67)
Experience		-0.007	-0.995***		
		(0.01)	(0.15)		
Expwithfirm		0.051**	0.014	-0.002	0.105***
		(0.02)	(0.02)	(0.02)	(0.02)
Coveragesize		-0.188***	-0.074**	-0.003	-0.008
		(0.03)	(0.03)	(0.03)	(0.03)
Coveragefocus		0.411***	0.122**	0.091*	0.092*
		(0.04)	(0.05)	(0.05)	(0.05)
Forecastfreq_Lag		0.032***	0.050***	0.003	0.004
		(0.01)	(0.01)	(0.01)	(0.01)
Top_Broker		0.408*	-0.105	-0.170	-0.317
		(0.21)	(0.58)	(0.58)	(0.57)
Size		-0.006***	-0.007***	-0.007***	0.008
		(0.00)	(0.00)	(0.00)	(0.01)
MTOB		-1.223	-0.667	-0.469	0.291
		(0.88)	(0.87)	(0.87)	(0.90)
Leverage		3.990*	2.321	2.425	1.077
		(2.33)	(2.09)	(2.07)	(2.04)

ROA		-12.531***	-8.716***	-8.968***	-4.185*
		(3.77)	(2.58)	(2.45)	(2.40)
Earngrowth		7.350***	4.782**	4.784**	1.480
		(2.28)	(2.09)	(2.05)	(1.99)
Instown		-2.507***	-2.430***	-2.714***	-0.224
		(0.43)	(0.42)	(0.42)	(1.15)
BM		-0.098*	0.007	-0.085	-0.253***
		(0.05)	(0.05)	(0.05)	(0.07)
RD		14.103***	8.547***	6.786**	2.028
		(2.21)	(2.64)	(2.64)	(3.83)
Analyst FE			Y	Y	Y
Year Month FE				Y	Y
Firm FE					Y
Adjusted R^2	0.002	0.015	0.047	0.057	0.079
No. of observations	293,501	259,052	259,033	259,033	259,018

Table 5: Falsification Test by Hispanic and Female financial analysts

This table reports the results of falsification tests whereby regressing the measure for relative forecast boldness, *Boldrel* against placebo treatment dummies, *Female* and *Hispanic*, respectively, in the DiD setting. *Hispanic* is a dummy variable that takes the value of unity for Hispanic financial analysts and zero otherwise. *Female* is a dummy variable that takes the value of unity for female financial analysts and zero otherwise. We control the same variables as that in Table 4. The sample is at analyst forecast level and ranges from March 2019 through November 2021. The results are estimated by linear regressions with different granular fixed effects, and standard errors are two-way clustered at the analyst-firm level. Standard errors are in the parentheses and *, **, *** denote levels of significance at 10%, 5% and 1%, respectively.

Panel A: Hispanic Financial Analysts

	(1)	(2)	(3)	(4)	(5)
Post×Hispanic	-0.454	-0.618	-0.438	-0.827	-0.145
	(1.45)	(1.46)	(1.54)	(1.47)	(1.39)
Post	2.254***	2.187***	3.681***		
	(0.16)	(0.17)	(0.25)		
Hispanic	0.101	0.348			
	(1.20)	(1.21)			
Controls		Y	Y	Y	Y
Analyst FE			Y	Y	Y
Year Month FE				Y	Y
Firm FE					Y
Adjusted R^2	0.001	0.014	0.047	0.058	0.080
No. of observations	253,193	223,709	223,690	223,690	223,665

Panel B: Female Financial Analysts

	(1)	(2)	(3)	(4)	(5)
Post×Gender	-0.093	-0.190	-0.371	-0.307	-0.165
	(0.48)	(0.49)	(0.50)	(0.49)	(0.49)
Post	2.153***	2.106***	3.355***		
	(0.16)	(0.17)	(0.24)		
Gender	0.055	-0.007			
	(0.43)	(0.44)			
Controls		Y	Y	Y	Y
Analyst FE			Y	Y	Y
Year Month FE				Y	Y
Firm FE					Y
Adjusted R^2	0.001	0.015	0.047	0.057	0.079
No. of observations	293,501	258,851	258,832	258,832	258,817

Table 6: Mechanism Analysis Using Staggered DiD

This table reports the results of channel and mechanism analyses whereby regressing in a (weighted) staggered DiD setting the measure for relative forecast boldness, *Boldrel*, against the measures of Anti-Asian hate crimes and COVID-19 situations respectively in Panels A and B, and together in Panel C. *Crime* is the continuous Anti-Asian hate crime measure that accumulates the number of incidents identified in the state of the analyst within two weeks prior to her forecast. *Pos_Cases* is a dummy variable that takes the value of unity if the growth rate of 7 days moving average is negative and zero otherwise. We control the same variables as those in Table 4. The sample is at analyst forecast level and ranges from March 2019 through November 2021. The results are estimated by linear regressions with different granular fixed effects, and standard errors are two-way clustered at the analyst-firm level. Standard errors are in the parentheses and *, **, *** denote levels of significance at 10%, 5% and 1%, respectively.

Panel A: The number of hate crime incidents against Asians (*Crime*)

	(1)	(2)	(3)	(4)	(5)
Crime×East_Asian	-0.134**	-0.170***	-0.129**	-0.119**	-0.142***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Crime	0.598***	0.604***	0.690***	0.254***	0.250***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
East_Asian	2.097***	1.675***			
	(0.30)	(0.31)			
Controls		Y	Y	Y	Y
Analyst FE			Y	Y	Y
Year Month FE				Y	Y
Firm FE					Y
Adjusted R^2	0.006	0.019	0.051	0.058	0.079
No. of observations	293,501	259,052	259,033	259,033	259,018

Panel B: Positive Momentum of COVID-19 New Cases (*Pos_Cases*)

	(1)	(2)	(3)	(4)	(5)
East_Asian×Pos_Cases	0.230	0.021	-0.230	-0.117	-0.295
	(0.37)	(0.40)	(0.39)	(0.38)	(0.38)
Pos_Cases	1.765***	1.836***	1.685***	0.305*	0.343*
	(0.14)	(0.15)	(0.15)	(0.18)	(0.18)
East_Asian	1.866***	1.449***			
	(0.29)	(0.30)			
Controls		Y	Y	Y	Y
Analyst FE			Y	Y	Y
Year Month FE				Y	Y
Firm FE					Y

Adjusted R^2	0.001	0.015	0.046	0.057	0.079
No. of observations	293,501	258,851	258,832	258,832	258,817

Panel C: Horse Race Between Anti-Asian Crimes and COVID-19 Situation

	(1)	(2)	(3)	(4)	(5)
East_Asian ×Neg_Cases	0.409	0.314	-0.078	0.015	-0.126
	(0.38)	(0.41)	(0.40)	(0.40)	(0.40)
Neg_Cases	0.649***	0.683***	0.671***	0.093	0.145
	(0.15)	(0.15)	(0.15)	(0.18)	(0.18)
Crime×East_Asian	-0.130**	-0.163***	-0.106*	-0.102*	-0.121**
	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)
Crime	0.574***	0.577***	0.669***	0.251***	0.246***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
East_Asian	1.859***	1.448***			
	(0.32)	(0.33)			
Controls		Y	Y	Y	Y
Analyst FE			Y	Y	Y
Year Month FE				Y	Y
Firm FE					Y
Adjusted R^2	0.006	0.019	0.051	0.058	0.079
No. of observations	293,501	258,851	258,832	258,832	258,817

Table 7: Additional Measures of Forecast Quality

This table reports the additional results of additional analyst forecast quality measures against the treatment dummy, *Asian*, in a DiD setting. In Panel A, *Pessimism* is a dummy variable that takes the value of unity if the analyst's forecast is below its past 180 days average. In Panel B, *RecChg* is a trinary variable equal to one if an analyst upgrades its previously outstanding forecast, zero if there is no change, and negative one for downgrades. In Panel C, *Frequency* is the number of updated forecasts issued by an analyst in a month for a focal firm. This specification is at firm-analyst-month level. In Panel D, *Timeliness* is the negative value of the number of days between the last earnings announcement date and analyst forecast date after that. In Panel E, *Forecast Error* is the absolute difference between the forecasted EPS and the realized EPS, divided by the stock's price 12 months prior to the quarterly earnings announcement date. We control the same variables as that in Table 4. The sample is at the analyst forecast level and ranges from March 2019 through November 2021. The parameter estimates are conducted by linear regressions with different granular fixed effects, and standard errors are two-way clustered at the analyst-firm level. Standard errors are in the parentheses and *, **, *** denote levels of significance at 10%, 5% and 1%, respectively.

Panel A: Forecast Pessimism as Measured by *Pessimism*

	(1)	(2)	(3)	(4)	(5)
Post×East_Asian	0.007	0.016*	0.023***	0.022**	0.017**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Post	-0.064***	-0.073***	0.036***		
	(0.00)	(0.00)	(0.00)		
East_Asian	-0.010	-0.009			
	(0.01)	(0.01)			
Controls		Y	Y	Y	Y
Analyst FE			Y	Y	Y
Year Month FE				Y	Y
Firm FE					Y
Adjusted R^2	0.004	0.014	0.056	0.082	0.119
No. of observations	305,966	269,454	269,434	269,434	269,430

Panel B: Forecast Pessimism as Measured by *Rec_Chg*

	(1)	(2)	(3)	(4)	(5)
Post×East_Asian	-0.027***	-0.031***	-0.035***	-0.032***	-0.025**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Post	0.140***	0.154***	0.003		
	(0.00)	(0.00)	(0.01)		
East_Asian	0.023***	0.025***			
	(0.01)	(0.01)			
Controls		Y	Y	Y	Y

Analyst FE			Y	Y	Y
Year Month FE				Y	Y
Firm FE					Y
Adjusted R^2	0.007	0.010	0.035	0.071	0.096
No. of observations	305,966	269,454	269,434	269,434	269,430

Panel C: Updating Frequency

	(1)	(2)	(3)	(4)	(5)
Post×East_Asian	-0.218	-0.627	-0.574	-0.558	-0.828**
	(0.51)	(0.48)	(0.39)	(0.37)	(0.36)
Post	2.366***	1.330***	3.859***		
	(0.18)	(0.18)	(0.24)		
East_Asian	-5.068***	-3.735***			
	(0.47)	(0.44)			
Controls		Y	Y	Y	Y
Analyst FE			Y	Y	Y
Year Month FE				Y	Y
Firm FE					Y
Adjusted R^2	0.018	0.166	0.498	0.589	0.643
No. of observations	34,142	29,534	29,497	29,497	29,384

Panel D: Timeliness

	(1)	(2)	(3)	(4)	(5)
Post×East_Asian	-0.659*	-0.819**	-0.968**	-0.966**	-1.151***
	(0.38)	(0.40)	(0.41)	(0.41)	(0.40)
Post	1.334***	1.776***	3.247***		
	(0.14)	(0.15)	(0.23)		
East_Asian	-0.148	0.038			
	(0.35)	(0.35)			
Controls		Y	Y	Y	Y
Analyst FE			Y	Y	Y
Year Month FE				Y	Y
Firm FE					Y
Adjusted R^2	0.000	0.006	0.029	0.047	0.062

No. of observations	304,297	268,856	268,837	268,837	268,834

Panel E: Forecast Error

	(1)	(2)	(3)	(4)	(5)
Post×East_Asian	-0.006	0.006	-0.003	0.002	0.011*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Post	0.002*	0.002*	0.006***		
	(0.00)	(0.00)	(0.00)		
East_Asian	0.014***	0.009*			
	(0.01)	(0.01)			
Controls		Y	Y	Y	Y
Analyst FE			Y	Y	Y
Year Month FE				Y	Y
Firm FE					Y
Adjusted R^2	0.000	0.047	0.072	0.072	0.323
No. of observations	265,297	238,422	238,406	238,406	238,405

Table 8: Deteriorating Asian Analyst Forecast and Information Efficiency

This table reports the empirical results of examining the effect of deteriorating forecast boldness of Asian financial analysts on analyst herding and consensus forecast accuracy. *Herding* is a dummy variable that takes the value of one for a forecast which is between the analyst's own prior forecast and the consensus forecast, and zero otherwise. *Relative_Accuracy* is the average of the difference between the median forecast error of all analysts following a firm and the analyst's forecast error following the firm, scaled by the standard deviation of the forecast error of all analysts following the firm. *Absolute_Accuracy* is the difference of the mean EPS forecast and the real EPS, scaled by the real EPS. *Economic_Tie* is the sector volume of US-China international trade to control a firm's exposure to China and Asian analysts' high tendency to cover firms with a strong economic tie to China. Since we control Year Quarter fixed effect, *Post* is absorbed. The sample is at firm-fiscal quarter level and ranges from March 2019 through November 2021. Standard errors are two-way clustered at the analyst-firm level. Standard errors are in the parentheses and *, **, *** denote levels of significance at 10%, 5% and 1%, respectively.

	Herding	*Herding*	*Relative_Accuracy*	*Relative_Accuracy*	*Absolute_Accuracy*	*Absolute_Accuracy*
	(1)	(2)	(3)	(4)	(5)	(6)
Boldrel_Asian	-0.030***	-0.068***				
	(0.01)	(0.01)				
Herding			-0.004***	-0.004***	0.003**	0.003*
			(0.00)	(0.00)	(0.00)	(0.00)
Economic_Tie	-0.430	4.549	-0.251	-0.042	0.388	-0.127
	(9.31)	(9.77)	(0.45)	(0.46)	(1.90)	(2.10)
Controls	Y	Y	Y	Y	Y	Y
Industry FE	Y		Y		Y	
Firm FE		Y		Y		Y
Year Quarter FE	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.229	0.378	0.137	0.278	0.114	0.260
No. of observations	25,982	25,741	25,882	25,637	22,933	22,615

Table 9: Market Reaction to Deteriorating Asian Analyst Forecast

This table reports the empirical results of examining the influence of Asian financial analysts and their deteriorating forecast quality on valuation and market efficiency through mediating analysis. The dependent variables, *Abnormal_Return,* are post-earnings announcement buy-and-hold abnormal returns over various windows (5 days, 10 days, 15 days, and 30 days) benchmarked by Fama-French three-factor model. Since we control Year Month fixed effect, *Post* is absorbed. The sample is at the firm-fiscal quarter level and ranges from March 2019 through November 2021. Standard errors are two-way clustered at the analyst-firm level. Standard errors are in the parentheses and *, **, *** denote levels of significance at 10%, 5% and 1%, respectively.

	Abnormal_Return[0,5]	*Abnormal_Return*[0,10]	*Abnormal_Return*[0,15]	*Abnormal_Return*[0,30]
	(1)	(3)	(5)	(7)
Post×East_Asian	-0.017***	-0.025***	-0.025***	-0.038***
	(0.01)	(0.01)	(0.01)	(0.01)
East_Asian	0.004	0.007	0.005	-0.000
	(0.01)	(0.01)	(0.01)	(0.01)
Analyst_Count	-0.001***	-0.002***	-0.001***	-0.001**
	(0.00)	(0.00)	(0.00)	(0.00)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year Month FE	Y	Y	Y	Y
Adjusted R^2	0.274	0.268	0.278	0.277
No. of observations	24,331	24,333	24,335	24,336

Table 10: Robustness Test Using More Granular Fixed Effects

This table reports the empirical results of the original DiD specification of *Boldrel* against *East_Asian* by including more granular fixed effects. *Boldrel* is the main variable of interest and an impotant indicator of forecast quality. We control the same variables as that in Table 4. The sample is at analyst forecast level and ranges from March 2019 through November 2021. Standard errors are two-way clustered at the analyst-firm level. Standard errors are in the parentheses and *, **, *** denote levels of significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)
Post×East_Asian	-2.353***	-3.059***	-3.084***	-3.265***
	(0.75)	(0.76)	(0.81)	(0.87)
Controls	Y	Y	Y	Y
Analyst-Year FE	Y	Y	Y	Y
Year Month FE	Y	Y	Y	Y
Firm FE	Y			
Analyst-Firm-Fiscal Quarter FE		Y	Y	Y
Earning Announcement FE		Y	Y	Y
City FE	Y	Y	Y	Y
Adjusted R^2	0.097	0.177	0.354	0.380
No. of observations	258,734	258,407	249,555	248,691

Table 11: Robustness test by Alternative Dependent Variables

This table reports the empirical results of regressing alternative dependent variables, *Bold_neg, Bold_pos,* and *Absolute Boldness* against *East_Asian*, respectively, in the original DiD setting. In panel A, *Bold_pos*, is a dummy variable that takes the value of unity if an analyst's forecast is above both the analyst's own prior forecast and the consensus forecast immediately prior to the analyst's forecast and zero otherwise. In panel B, *Bold_neg*, is a dummy variable that takes the value of unity if an analyst's forecast is below both the analyst's own prior forecast and the consensus forecast immediately prior to the analyst's forecast, and zero otherwise. In panel C, *Absolute Boldness*, is the absolute difference between an analyst's most recent earnings forecast for a firm in the first 2 months of a quarter and the average consensus earnings forecast made by all other analysts covering the firm (following Chang, Ljungqvist, and Tseng, 2023). We control the same variables as that in Table 4. The sample is at analyst forecast level and ranges from March 2019 through November 2021. Standard errors are two-way clustered at the analyst-firm level. Standard errors are in the parentheses and *, **, *** denote levels of significance at 10%, 5% and 1%, respectively.

Panel A: Relative negative boldness as measured by the dummy variable *Bold_neg*

	(1)	(2)	(3)	(4)	(5)
Post×East_Asian	0.004	0.011*	0.016***	0.015**	0.011*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Controls		Y	Y	Y	Y
Analyst FE			Y	Y	Y
Year Month FE				Y	Y
Firm FE					Y
Adjusted R^2	0.002	0.053	0.086	0.128	0.155
No. of observations	305,966	269,454	269,434	269,434	269,430

Panel B: Relative positive boldness as measured by *Bold_pos*

	(1)	(2)	(3)	(4)	(5)
Post×East_Asian	-0.017***	-0.016***	-0.016***	-0.015***	-0.011**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Controls		Y	Y	Y	Y
Analyst FE			Y	Y	Y
Year Month FE				Y	Y
Firm FE					Y
Adjusted R^2	0.011	0.044	0.077	0.102	0.133

No. of observations	305,966	269,454	269,434	269,434	269,430

Panel C: *Absolute Boldness*

	(1)	(2)	(3)	(4)	(5)
Post×East_Asian	-0.020***	-0.016**	-0.018**	-0.016**	-0.015**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Controls		Y	Y	Y	Y
Analyst FE			Y	Y	Y
Year Month FE				Y	Y
Firm FE					Y
Adjusted R^2	0.018	0.039	0.109	0.118	0.267
No. of observations	305,966	269,454	269,434	269,434	269,430