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EVIDENCE FROM AIRBNB

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Scapegoating and Discrimination in Times of Crisis: Evidence from Airbnb
Michael Luca, Elizaveta Pronkina, and Michelangelo Rossi
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ABSTRACT

We present evidence that discrimination against Asian-American Airbnb users sharply increased at the start of the COVID-19 pandemic. Using a DiD approach, we find that hosts with distinctively Asian names experienced a 12 percent decline in guests relative to hosts with distinctively White names. In contrast, we do not see spikes in discrimination against Black or Hispanic hosts. Our results suggest that the rise in anti-Asian sentiment in 2020 translated to discrimination in economic activity, highlighting the ways in which scapegoating minority groups can shape markets. Our results also point to the role of platform design choices in enabling discrimination.

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A data appendix is available at <http://www.nber.org/data-appendix/w30344>

1 Introduction

The COVID-19 pandemic originated in Wuhan, China, and quickly spread to the rest of the world. Although the COVID-19 related death rate was ultimately much lower in China relative to Europe and North America, the pandemic witnessed an increase in anti-Asian sentiment in the United States. According to a Pew Research Center survey (Ruiz, Edwards and Lopez, 2021), almost half of Asian American adults experienced at least one racist incident in the first year of the pandemic. Evidence from psychology research shows that anti-Asian sentiment and racial scapegoating grew with COVID-19 (Borja, Jeung, Horse, Gibson, Gowing, Lin, Navins and Power, 2020; Cheah, Wang, Ren, Zong, Cho and Xue, 2020; Tessler, Choi and Kao, 2020; Cheng, Kim, Tsong, Joel Wong et al., 2021).

High profile American conservative politicians and media also made frequent references associating the virus with China. For instance, in notes for a March 2020 speech, then President Donald Trump crossed out the word “Corona” in front of virus, and replaced it with the word “Chinese” - and went on to refer to COVID-19 as “the Chinese Virus”. Trump was engaging in scapegoating, seeking to blame the rapid spread of COVID-19 throughout the United States on China. On various occasions, he used racist language and stoked anti-Chinese sentiment - referring to COVID-19 as the “China Virus”, “Wuhan Virus”, and “Kung Flu.” As shown in Google search trends in Figure 1, searches for China Virus and Wuhan Virus were particularly common early in the pandemic. This rhetoric mirrored a broader rise in anti-Asian sentiment during the pandemic, and raised concerns of discrimination against Asian Americans and the formation of stereotypes associating Asian Americans with COVID-19. This is consistent with a recent body of evidence showing that periods of crisis increase scapegoating and activate antipathy toward minority groups (Fisman, Hamao and Wang, 2014; Fouka and Voth, 2016; Cantoni, Hagemeister and Westcott, 2019; Bursztyn, Egorov, Haaland, Rao and Roth, 2022).

In this paper, we use the COVID-19 outbreak in 2020 to study how salient events such as a pandemic can at times foster discrimination against a minority group in consumption decisions. To do so, we answer the following question: Did COVID-19 lead to discrimination against Asian-Americans in consumption decisions? We explore this question by looking at short-term housing rentals on Airbnb in New York City. We use a difference-in-differences (DiD) approach to compare

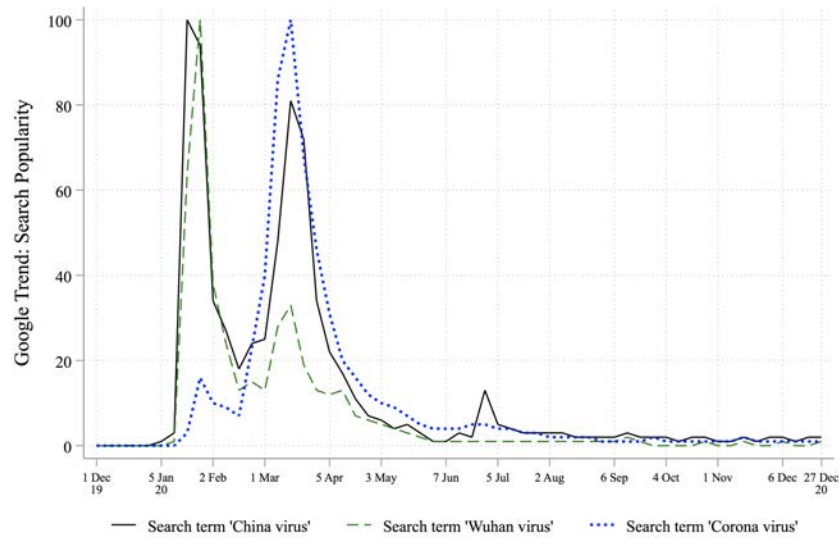


Figure 1: Google Trend of Searchers “China Virus”, “Wuhan Virus”, and “Corona Virus”

Notes: Search popularity is based on Google Trend statistics in the US.

the number of guests staying with Asian-American Airbnb hosts relative to other hosts, during the pandemic relative to the previous year.

Should we expect an increase in discrimination? In practice, Asian Americans have had a lower death rate from COVID-19 relative to White, Black, and Hispanic Americans.¹ Thus, an increase in discrimination would likely not reflect accurate statistical discrimination based on the actual risk of contagion. Yet, a growing literature (Jensen, 2010; Bursztyjn, González and Yanagizawa-Drott, 2020; Bohren, Haggag, Imas and Pope, 2019) has shown that discrimination can be often rooted in inaccurate beliefs, in contrast with early models of statistical discrimination (Arrow, 1973; Aigner and Cain, 1977). Beliefs about the risks involved in different activities during the pandemic have been noisy (Bundorf, DeMatteis, Miller, Polyakova, Streeter and Wivagg, 2021; Bordalo, Burro, Coffman, Gennaioli and Shleifer, 2022). Stereotypes simplify the representation of groups, which can lead to systematic errors in judgment (Tversky and Kahneman, 1983; Bordalo, Coffman, Gennaioli and Shleifer, 2016). Anti-minority sentiment can be further fueled by political rhetoric and scapegoating (Glaeser, 2005). The modern literature on scapegoating dates back at least to the Dreyfus Affair in France in 1899 (Durkheim, 1899), and has been studied within psychology since at least the mid twentieth century (Allport, Clark and Pettigrew, 1954).

¹According to a report by the Kaiser Family Foundation (Latoya and Samantha, 2022), Asian Americans are the ethnic group with the lowest share of COVID-19 cases and deaths compared to their population share.

Looking at panel data on Airbnb, we find that discrimination against Asian-American hosts sharply increased at the start of the COVID-19 pandemic. After January 2020, hosts with distinctively Asian names experienced a 12 percent decline in guests as proxied by reviews, relative to hosts with White-sounding names. With an event-study analysis, we show that 1) Asian and White Airbnb hosts follow comparable trends during 2019; and 2) the drop in the number of guests suffered by Asian hosts becomes notable in the Spring of 2020 and remains so through 2020.

Our results are robust to the inclusion of listing and time fixed effects. To separate anti-Asian bias from changing preferences across neighborhoods (which might be correlated with neighborhood demographics), we use time interacted with neighborhood fixed effects. We also use coarsened exact matching to ensure comparable properties in the treated (Asian) and control (White) groups. We match listings using dwelling characteristics, and pre-pandemic official statistics from the American Community Survey about the area in which each listing is located.

Airbnb allows hosts to reject guests booking requests. Accordingly, Asian hosts may have reacted to the pandemic by accepting fewer guests, which may result in a reduced number of transactions. To assess this hypothesis, we replicate our analysis using only hosts that have had active the “instant bookable” option. When this option is on, hosts automatically accept all guests requests. The sign and the size of the DiD estimates do not change for this subsample. Moreover, Asian hosts do not charge higher prices than White hosts after January 2020. Thus, the drop in the number of guests is not driven by changes on the platform supply side.

As an additional falsification exercise, we study the number of guests during the pandemic for Black and Hispanic hosts. We do not observe spikes in discrimination against Black or Hispanic hosts, relative to pre-pandemic levels - which further suggests that the results reflect the anti-Asian discrimination that increased during the pandemic.

Airbnb makes a compelling setting in which to study our research question. Airbnb is of direct interest as the world’s largest short-term accommodation provider, with a market capitalization of 70 billion dollars as of 2022. From a research perspective, online platforms such as Airbnb have important advantages in exploring economic phenomena. Airbnb provides the opportunity to observe the evolution of a market over time. In our data, we track all listings for the year before and after the pandemic began in New York City, which is a major market for Airbnb. Our data allows us to observe outcomes at the listing level, providing granular insight into booking patterns.

Overall, our results speak to the impact of crises such as the COVID-19 pandemic on discrimination. COVID-19 represented an unprecedented shock in terms of health, job losses, and productivity. Our analysis provides a window into economic activity in one of the world’s largest marketplaces, and demonstrates that the rise in anti-Asian sentiment early in the pandemic translated to significant discrimination in economic activity. Our work contributes to the literature on discrimination and highlights the role of crises in triggering discrimination against scapegoated groups in market settings.

Our results also contribute to the literature on market design. As a platform, Airbnb has made design choices that enable discrimination (Edelman, Luca and Svirsky, 2017; Ahuja and Lyons, 2019; Ameri, Rogers, Schur and Kruse, 2020; Cui, Li and Zhang, 2020; Laouénan and Rathelot, 2022). For instance, Airbnb makes the name of property owners salient in the process of choosing potential stays. This is in contrast with platforms such as Expedia. By making the ethnicity of users salient before a booking decision is made, Airbnb permits discrimination that would be more difficult had they not showed identifying information about users until after a booking is complete (Fisman and Luca, 2016). Our results provide novel insight into the ways in which increased racial bias can creep into a marketplace with discrimination-permissive design choices in times of crisis. As a market designer, Airbnb makes important decisions that shape the susceptibility of the platform to shocks that affect discrimination.

2 Empirical Context and Identification Strategy

The data comes from Inside Airbnb, a website tracking Airbnb listings present in many cities over time. We use data about New York City, one of the largest markets for Airbnb in the US, with no relevant policies affecting short-term rentals in its metropolitan area during 2019 and 2020. Our data is composed of monthly snapshots of Airbnb listings present in New York City from January 2019 to November 2020.² In total, our data is composed by 23 snapshots. Every month, we observe which listings appear on the Airbnb website at the snapshot date. For each listing observation, we have a set of characteristics such as the listing’s location (longitude and latitude);

²The Homesharing Surveillance Ordinance, a short-term rental regulation enacted by the New York City council, goes into effect in January 2021. We observe a drop in the number of Airbnb listings starting from December 2020 and we restrict our analysis until November 2020.

dwelling’s characteristics; the name of the host managing the listing; the total number of reviews posted by guests in the past; the average star ratings, and the per-night price. We complement this dataset with external official statistics. We use the official neighborhoods from the Department of City Planning of NYC and we assign listings to neighborhoods. Moreover, we add external statistics dated to 2018 (to isolate the endogenous changes to the timing of COVID-19) provided by U.S. Census Bureau in the American Community Survey (ACS) about the area in which each listing is located.

We proxy the number of guests staying with each listing in a specific month by the difference in the number of reviews posted between two consecutive snapshots. Thus, we restrict our analysis over listings that are present on the platform for at least two snapshots. To measure hosts’ race, we use information about hosts’ name.³ We apply a machine-learning algorithm (Ye, Han, Hu, Coskun, Liu, Qin and Skiena, 2017; Ye and Skiena, 2019) to identify the probability of a name belonging to different races.⁴ We focus on the four most common races: Asian, Black, Hispanic, and White. We consider a host to belong to one race if the name-based probability of being of that race is greater than 0.9 - and vary this threshold in our robustness checks.

The aim of this study is to estimate the magnitude of the discrimination against Asian hosts and the associated drop in the number of reviews during the first year of the COVID-19 pandemic. To do so, we compare Asian and White hosts in 2019 and 2020. Before turning on the description of the DiD strategy, we briefly present descriptive statistics about these two groups. In Appendix Table A.1, we present summary statistics about all hosts active on the platform between January 2019 and November 2020; and only hosts with distinctive Asian and White names. There are 913 hosts (2.5% of the total) with distinct Asian names and 15,748 hosts (41%) with distinct White names in New York City during this period. Asian hosts tend to receive more reviews than White hosts. They also tend to select the “instant bookable” option more often. Accordingly, they are more likely to accept guests’ booking requests: this may partially explain the higher number of reviews for this group. Hosts tend to be located in areas with a larger percentage of residents of their race. White hosts are located in areas with fewer minority groups relative to Asian hosts, and in particular, Black and Hispanic hosts, as we can see in Appendix Table A.2. In Appendix Figure

³We consider only the first listed name when hosts include several names (less than 5% of all hosts).

⁴We highly appreciate access to the NamePrism classifier algorithm provided by Prof. Steven Skiena: <http://name-prism.com/about>.

A.1, we illustrate the evolution of the number of reviews for Asian and White hosts during 2019 and 2020. On average, Asian hosts tend to have more reviews than White hosts before January 2020. The drop in the demand due to the COVID-19 outbreak affects all Airbnb hosts, but it is much larger for Asian hosts. In particular, after April 2020, White hosts have slightly more reviews than Asian hosts. This preliminary analysis about the number of reviews over time presents the main result to be formalized with our empirical strategy: Asian hosts suffer a strong reduction in their economic activity on the platform during the first months of the COVID-19 pandemic.

To capture discrimination against Asian hosts during the COVID-19 pandemic, we use the following DiD specification:

$$Reviews_{it} = \alpha_1 + \alpha_2 Asian_i + \alpha_3 After_t + \delta Asian_i \times After_t + \beta X_{it} + \varepsilon_{it}, \quad (2.1)$$

where $Reviews_{it}$ is the number of reviews listing i receives between snapshot t and the previous snapshot in which listing i was present on the platform. In our preferred specification, $Asian_i$ is a dummy variable equal to 1 if the probability to be Asian for the host managing listing i is greater than 0.9; and equal 0 if the probability to be White is greater than 0.9. $After_t$ is equal to 1 for all snapshots after January 2020; and equal to 0 otherwise. The set of controls X_{it} includes listing fixed effects, neighborhood-by-time fixed effects, neighborhood-specific time trends and separate trends for Asian and White hosts.

The coefficient δ captures discrimination against Asian hosts under the assumption that White hosts provide a good counterfactual for the evolution of the number of guests during the COVID-19 pandemic. Accordingly, we assume guests' propensity to write reviews does not vary for Asian hosts relative to White hosts in response to the outbreak of COVID-19. To show the absence of potential pre-trends between treated and control groups, we illustrate the evolution of $Reviews_{it}$ over time with an event-study approach. We consider the following lead-lag model in which $Reviews_{it}$ is regressed over the product between the dummy $Asian_i$ and a full set of dummy variables for each snapshot. The model controls for listing fixed effects; neighborhood-by-time fixed effects and neighborhood-specific time trends:

$$Reviews_{it} = \alpha_i + \rho_t + \sum_{\tau=Jan19}^{Nov20} \delta_{\tau} Asian_i \times 1(t = \tau) + \varepsilon_{it}. \quad (2.2)$$

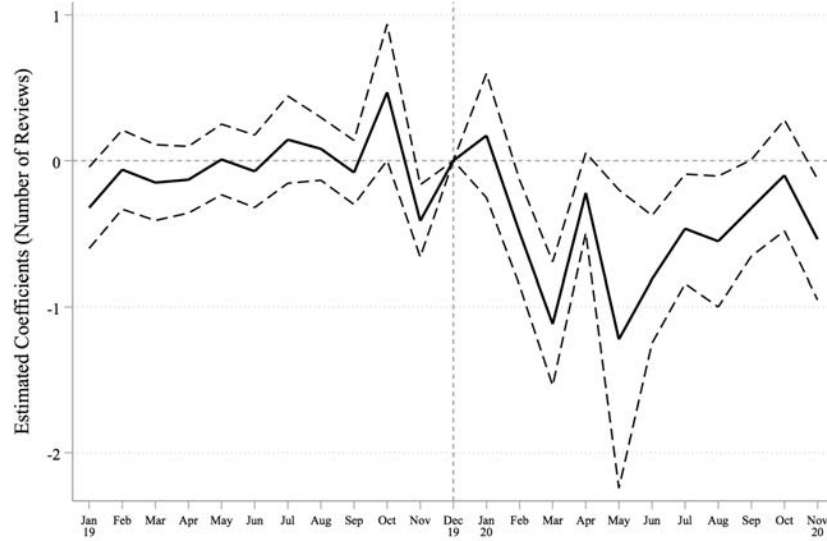


Figure 2: Event study: Number of Reviews - Asian and White Hosts

Notes: In line with Equation 2.2, $Reviews_{it}$ is regressed on listing fixed effects; neighborhood-by-time fixed effects, neighborhood-specific time trends, and on the products between $Asian_i$ and a full set of dummy variables for each snapshot. The graph plots the estimated coefficients on these products. The value of the coefficient corresponding to December 2019 is normalized to zero. The sample includes snapshots between January 2019 and November 2020 for listings located in New York and managed by hosts with a name-based probability of being Asian or White greater than 0.9. Standard errors (10%) are clustered by listing.

We present the results of the estimates of Equation 2.2 in Figure 2 where we plot the estimated δ_τ from January 2019 to November 2020. Before January 2020, the coefficients are close to zero and they do not exhibit a clear trend. Thus, the evolution of the number of reviews for listings managed by Asian and White hosts was similar before the pandemic. After January 2020, the coefficients are negative and the number of reviews drops for Asian hosts relative to White hosts. The effect is persistent over 2020. Yet, the reduction is particularly notable in Spring 2020 when the association between COVID-19 and China was the strongest.

3 Impact on Asian-American Hosts

3.1 Main Results

We now present the main empirical results. Table 1 shows four specifications for the DiD estimates in Equation 2.1. The outcome variable is the number of reviews received between two snapshots. The sample includes snapshots between January 2019 and November 2020 for listings located in

New York City and managed by hosts with a name-based probability of being Asian or White greater than 0.9. We cluster standard errors at listing level.⁵

In Column (1) we use listing fixed effects, time fixed effects, and a linear trend. The listing fixed effects remove all time-invariant elements such as dwellings' and geographical area characteristics; the time fixed effects and the time trend account for time-varying confounders that affect all listings in the same way. For instance, the COVID-19 outbreak and the related lockdowns have determined a sharp drop in demand for all listings in New York. However, this drop might not be the same across neighborhoods in the city. In Column (2) we include neighborhood-by-time fixed effects to allow for differential time variations in the demand for short-term rentals across neighborhoods. On top of mentioned controls, in Column (3) we add separate time trends for Asian and White hosts to sort out the demand effect after January 2020 from medium-run tendencies of different ethnic groups. The estimates of the coefficient δ in Equation 2.1 are negative and significant for all specifications. The drop in the number of reviews suffered by Asian hosts is equal to 0.362 reviews which accounts for more than a 12% relative to the mean.

Asian and White hosts may differ, as suggested by descriptive statistics in Section 2. We use coarsened exact matching (Iacus, King and Porro, 2012) to make sure treated and control units are comparable. For the matching, we use time-invariant listings characteristics and official statistics from the Census American Community Survey in 2018 about the area where a listing is located.⁶ By doing so, 10% of the sample is removed due to imbalance between Asian and White hosts. In Column (4) we repeat the specification from Column (3) for the balanced subsample. This analysis confirms the evidence of Anti-Asian discrimination with a significant drop in the number of reviews suffered by Asian hosts.

To support the estimated decline in the number of transactions suffered by Asian hosts, we perform multiple robustness checks. So far, hosts are labeled as Asian or White if the name-based probability of their corresponding race group is above 0.9. The results are robust to using different cutoff levels to determine the hosts' race. Appendix Table A.3 show the DiD estimates when we vary the cutoff levels from 0.95 to 0.8. With narrow cutoffs, the sample size decreases. Yet,

⁵The results are robust to clustering the errors at a neighborhood level or at a Census Survey area level.

⁶The listing characteristics used for the matching are the following: whether the listing rents an entire house or a single room; whether it is used for short-term rentals (guests can stay for less than 30 consecutive days); how many guests it can accommodate; and the number of bedrooms. The area's official statistics include the median income and the percentage of Asian residents of the public use microdata area where the listing is located.

Table 1: Difference-in-Differences: Number of Reviews - Asian and White Hosts

| | (1) | (2) | (3) | (4) |
|----------------------------------|----------------------|----------------------|---------------------|---------------------|
| Host Asian \times After Jan 20 | -0.362*** (0.126) | -0.359*** (0.128) | -0.402** (0.171) | -0.358** (0.169) |
| Listing FEs | ✓ | ✓ | ✓ | ✓ |
| Time FEs | ✓ | | | |
| Neighborhood \times Time FEs | | ✓ | ✓ | ✓ |
| Race-Specific Time Trends | | | ✓ | ✓ |
| CEM | | | | ✓ |
| R^2 | 0.427 | 0.450 | 0.450 | 0.484 |
| N | 111,902 | 111,902 | 111,902 | 101,285 |
| Mean Dep. Var. | 2.834 | 2.834 | 2.834 | 2.851 |

Notes: The sample includes snapshots between January 2019 and November 2020 for listings located in New York and managed by hosts with a name-based probability of being Asian or White greater than 0.9. “Neighborhood \times Time FEs” include neighborhood-by-time fixed effects and neighborhood-specific time trends. “Race-Specific Time Trends” include separate time trends for Asian and White hosts. The coarsened exact matching (“CEM”) in Column (4) is based on time-invariant listing characteristics and official statistics from the American Community Survey in 2018 about the area where a listing is located. Standard errors clustered by listing are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

names are now a more precise signal of hosts’ race and guests could better identify and discriminate against Asian hosts. As a result, the coefficients δ become larger and the size of the effect increases to 15% when we use the strictest cutoff of 0.95. Regardless of the chosen level, the DiD estimate remains statistically significant at a 5 percent level.

Next, we study if the drop in the number of reviews is driven by the selection of hosts during the pandemic. Asian and White hosts enter and exit the platform over time. Thus, variations in the profile of listings that are managed by Asian and White hosts may partially explain our effect. For instance, very attractive listings managed by Asian hosts may exit the platform before the pandemic and determine a reduction in the number of interested guests for this minority group. To account for listing selection, we restrict our analysis to hosts who are present on Airbnb before and after January 2020. With this subsample, we can match listings using pre-pandemic time-varying listings characteristics such as prices and ratings. The sample size decreases by 15%. Yet, the size and significance of the DiD estimates remain similar to the baseline 12% drop, as we can see in the Appendix Table A.4.

Up to now, we use the difference in the number of displayed reviews on the host’s webpage

over time as the main outcome variable. Yet, our results are robust to using alternative measures of guests' demand, as we show in Appendix Table A.5. In Column (1) we repeat the specification in Table 1 for comparison. In Column (2) we use the number of written comments posted by guests on the listings' webpage over time. In Column (3) we adjust the number of reviews for the number of days between two snapshots to get a measure of the number of reviews per day. We confirm that Asian hosts suffer a negative and significant shock in demand measured in terms of comments or reviews per day. The size of the effects is similar to the baseline estimate.

In the remaining part of this Section, we show that the reduction in the number of guests by Asian hosts is not due to supply-side effects such as the hosts' decisions to reject guests' booking requests; or ethnic-specific pricing strategies during the pandemic. As a falsification test, we show that other minorities (that were not directly associated with COVID-19) do not suffer significant drops in the number of reviews compared to White hosts. Moreover, we find similar evidence of Anti-Asian discrimination comparing Asian hosts with Black and Hispanic hosts.

3.2 Supply-Side Factors

“Instant Bookable” Hosts. The main results document a significant reduction in the number of reviews suffered by Asian hosts in the first months of 2020. We interpret this result as direct evidence of the surging Anti-Asian discrimination. However, Asian hosts may have reacted to the pandemic, being less willing to accept Airbnb guests after the outbreak of COVID-19. To check whether this supply-side channel drives our results, we repeat the analysis focusing on Airbnb listings that were “instant bookable” during the whole period under analysis. The “instant booking” is a free option that each host can activate or deactivate at any time. “Instant bookable” listings automatically accept all guests' requests. With “instant booking” off, guests' requests to stay are subject to the host's approval.

We present the results of the event study for only “instant bookable” hosts in Figure 3 where we plot the estimated δ_τ of Equation 2.2 from January 2019 to November 2020. When we restrict the analysis to always “instant bookable” hosts, the sample size decreases from 111,902 observations to 35,776 observations.⁷ Despite this data loss, the drop in the number of reviews by Asian hosts is

⁷In our sample, 35% of hosts had always instant booking option on, 45% - always off and 20% - changed the status. The probability of activating the “instant booking” option by Asian and White hosts does not significantly

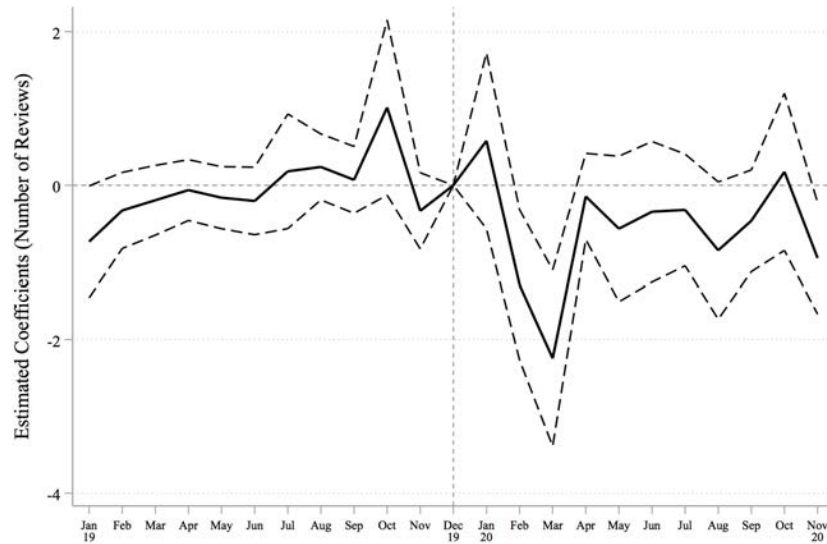


Figure 3: Event study: Number of Reviews - “Instant Bookable” Asian and White Hosts

Notes: In line with Equation 2.2, $Reviews_{it}$ is regressed on listing fixed effects; neighborhood-by-time fixed effects, neighborhood-specific time trends, and on the products between $Asian_i$ and a full set of dummy variables for each snapshot. The graph plots the estimated coefficients on these products. The value of the coefficient corresponding to December 2019 is normalized to zero. The sample includes snapshots between January 2019 and November 2020 for listings located in New York and managed by hosts with a name-based probability of being Asian or White greater than 0.9. We restrict to hosts who are always “instant bookable” during the period of analysis. Standard errors (10%) are clustered by listing.

still observable, with a notable spike during Spring 2020. The results of the DiD specification are reported in Appendix Table A.6. The reduction in the number of reviews suffered by Asian hosts who cannot reject guests’ requests is statistically significant and of a larger magnitude relative to the baseline specification: “instant bookable” Asian hosts experience a decline of more than 20% in their number of reviews. Accordingly, non-“instant bookable” Asian hosts were less penalized during the pandemic than their “instant bookable” counterparts. A possible interpretation of this result is that non-“instant bookable” Asian hosts became more willing to accept Airbnb guests compared to White hosts after the pandemic. Facing an hostile environment with a drop in demand, they became less selective to reduce the adverse effects of discrimination.

Prices. Can the drop in the number of reviews for Asian hosts be due to their pricing strategy? One might be concerned about the possibility that Asian-American hosts could have increased their prices after the outbreak of COVID-19 more than other groups. In that case, they might change during the COVID-19 pandemic. To show this, we repeat our DiD strategy using the “instant booking” status as the outcome variable.

be less likely to attract guests, resulting in fewer transactions and reviews because of supply-side effects. To explore this hypothesis, when we restrict our analysis to hosts present before and after January 2020, we match listings using pre-pandemic average prices and ratings (Appendix Table A.4, Column 4). The drop in the number of reviews remains significant and of a similar magnitude to the baseline effect. When we control for prices in all specifications in Table 1, the DiD estimates remain similar in size and significance.

Moreover, we repeat the DiD analysis for the per-night prices. Appendix Table A.7 shows that the DiD estimate is not statistically significant. This result suggests that Asian hosts do not significantly alter their pricing decisions during the COVID-19 pandemic relative to White hosts.

3.3 Impact on Black-American and Hispanic-American Hosts

The discrimination narrative during the COVID-19 outbreak was mainly directed against Asians. Other minorities were not the focus of the scapegoating rhetoric that was meant to associate the spread of the virus with China. We can run a falsification test to check whether the reduction in the number of guests suffered by Asian hosts is the result of the anti-Asian sentiment rising in the US, or it depends on a generalized antipathy towards all minorities. To which extent the decline in demand during 2020 is present only among Asian hosts? Do other minorities experience a similar drop in the number of transactions? To answer these questions, we use the same DiD identification strategy, using other minorities as the treated group. In line with the baseline specification, we label hosts as Black, or Hispanic if the name-based probability of being of the corresponding race is greater than 0.9. As before, the control group includes White hosts.

Table 2 shows the results. Column (1) is the baseline estimate for Asian hosts to ease the comparison of the size of the effects. Columns (2) and (3) report the results including Black and Hispanic hosts in the treated group, respectively. Both estimates are not statistically significant suggesting that hosts from other minorities did not suffer a reduction in the number of guests compared to White hosts. This result is consistent with our interpretation that there was an increase in discrimination on the platform against Asian-American hosts, relative to other groups.

To reinforce this last point, we can show that Asian hosts witnessed a reduction in the number of reviews during the pandemic relative to the other minorities as well. To do that, we repeat

Table 2: Falsification Test: Number of Reviews - Different Minorities and White Hosts

| | (1) | (2) | (3) |
|-------------------------------------|----------------------|-------------------|------------------|
| Host Asian \times After Jan 20 | -0.359*** (0.128) | | |
| Host Black \times After Jan 20 | | -0.063 (0.151) | |
| Host Hispanic \times After Jan 20 | | | 0.026 (0.108) |
| Listing FEs | ✓ | ✓ | ✓ |
| Neighborhood \times Time FEs | ✓ | ✓ | ✓ |
| R^2 | 0.450 | 0.446 | 0.444 |
| N | 111,902 | 107,345 | 110,643 |
| Mean Dep. Var. | 2.834 | 2.822 | 2.827 |
| Treated Group | Asian | Black | Hispanic |

Notes: The sample includes snapshots between January 2019 and November 2020 for listings located in New York and managed by hosts with a name-based probability of being White, or Asian (Column 1), Hispanic (Column 2), and Black (Column 3) greater than 0.9. “Neighborhood \times Time FEs” include neighborhood-by-time fixed effects and neighborhood-specific time trends. Standard errors clustered by listing are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the baseline DiD design using Black and Hispanic hosts as a control group. Appendix Table A.8 shows the result varying the minority groups used as control. Column (1) reports the baseline specific (with White hosts as control) to ease the comparison. In Columns (2), (3), and (4) we use as a control Black hosts, Hispanic hosts, and Black and Hispanic hosts together. Since there are fewer minority hosts on Airbnb, the sample size decreases significantly for all the specifications. When we use only Black hosts as control, the results are not significant. However, the power of this specification is severely limited by the reduced number of Black hosts (less than 200 during the whole period of analysis). Conversely, Asian hosts experienced a significant drop in the number of reviews when we use as control Hispanic hosts, and Black and Hispanic hosts together. For this last specification, the Appendix Figure A.2 illustrates that the pretend assumption is satisfied.

4 Conclusion

Crises ranging from wars to pandemics can trigger heightened anti-minority sentiment and scapegoating. Antipathy toward outgroups during times of crisis is not new, and is often exacerbated

by political actors (Glaeser, 2005). After World War II, bias against individuals with Japanese origins was so severe that it increased the likelihood that Japanese Americans selected Americanized names for their children - for instance, Kenneth instead of Kenji (Saavedra, 2021). After the September 11 attacks, there was a rise in anti-Muslim and anti-Middle Eastern sentiment. For instance, investments in mutual funds managed by Middle Eastern fund managers declined after September 11 (Kumar, Niessen-Ruenzi and Spalt, 2015). Our work demonstrates the ways in which Asian-Americans - a scapegoated group in the COVID 19 pandemic - has suffered increased discrimination in market transactions in the world's largest short term rental marketplace.

Our analysis also contributes to a large psychology literature that has explored discrimination, scapegoating and social comparisons (Lindzey, 1950; Wills, 1981; Rothschild, Landau, Sullivan and Keefer, 2012). Recent theory and lab work have highlighted mechanisms that have the potential to increase discrimination during times of crisis. Crises can “activate” antipathies and prejudice against minorities. They could lead people to seek out “someone to blame” creating favorable circumstances for scapegoating narratives (Bursztyn et al., 2022). During crises, people may form inaccurate beliefs driven by lack of the relevant information. Crises often present new scenarios with considerable uncertainty, which can lead people to rely on associative recall to make decisions (Bordalo et al., 2022). In a model of associative recall, associations between the pandemic and Asians might cue guests to think more about COVID, which also has the potential exacerbate discrimination. The fact that the virus was in China before the United States may have contributed to inaccurate beliefs about the ultimate toll of the virus. Our analysis point to the potential importance of these forces in a managerial and policy relevant setting.

To shed further light on the nature of discrimination in our setting, we conduct an analysis on the heterogeneous effects in Appendix Figure A.3. We find that discrimination persists among hosts with higher and lower ratings, among “superhost” (who have more experience on the platform), among cheap and expensive places, and among hosts who are renting out their entire place (as opposed to sharing the listing). This suggests that bias occurs even for experienced Airbnb Asian hosts and in settings where interaction with hosts is minimal.

The pandemic has had a profound impact on public health and the economy, leading to a rise in remote work (Dingel and Neiman, 2020; Brynjolfsson, Horton, Ozimek, Rock, Sharma and TuYe, 2020; Bartik, Cullen, Glaeser, Luca and Stanton, 2020b), struggles among small businesses (Bar-

tik, Bertrand, Cullen, Glaeser, Luca and Stanton, 2020a), disruptions to schools (Jack, Halloran, Okun and Oster, Forthcoming). Our work shows that the scapegoating of Asians during the pandemic led to an increase in discrimination in a market setting. Our results can also be compared to results by Bacher-Hicks, Goodman, Green and Holt (Forthcoming), who find that the shift to remote schooling actually reduced the extent of both in-person and cyberbullying in schools. Their analysis is an example in which online engagement led to better social outcomes. In contrast, we find that discrimination against Asian Americans increased during the pandemic in the context of Airbnb.

Our results also have important implications for market designers. In contrast with traditional travel websites such as Expedia, Airbnb makes a host's race salient. In response to Edelman and Luca (2014) and Edelman et al. (2017), Airbnb reduced the salience of a host's picture, by removing it off of the initial search results page. However, the name and photograph of a host can still be seen on the main listing page, making it easier for users to discriminate. Our results highlight that design choices that are permissive of discrimination become particularly vulnerable to discrimination when there are spikes in anti-minority sentiment. If Airbnb were to only show a host's name after a booking is made, there would be less scope for discrimination in the booking decision.

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