nature human behaviour

Article

https://doi.org/10.1038/s41562-022-01493-6

The cost of anti-Asian racism during the COVID-19 pandemic

Received: 11 January 2022

Accepted: 2 November 2022

Published online: 19 January 2023

Check for updates

Justin T. Huang [1], Masha Krupenkin [2], David Rothschild [3] & Julia Lee Cunningham [4]

Anti-Chinese sentiment increased during the COVID-19 pandemic, presenting as a considerable spike in overt violence and hatred directed at Asian American individuals. However, it is less clear how subtle patterns of consumer discrimination, which are difficult to directly observe yet greatly impact Asian American livelihoods, changed through the pandemic. Here we examine this in the context of restaurants—ubiquitous small businesses that sell goods that are closely entwined with ethnicity. Using a series of surveys, online search trends and consumer traffic data, we find that Asian restaurants experienced an 18.4% decrease in traffic (estimated US$7.42 billion lost revenue in 2020) relative to comparable non-Asian restaurants, with greater decreases in areas with higher levels of support for Donald Trump. Our findings are consistent with the roles of collective blame, out-group homogeneity and ethnic misidentification in explaining how anti-China rhetoric can harm the Asian American community, underlining the importance of avoiding racism and stigmatization in political and public health communications.

Scholars have long documented patterns of labour discrimination against people of colour in the United States[1–6]. These forms of discrimination have substantial negative effects on communities of colour, denying social mobility to historically marginalized groups[7,8]. Even as some forms of discrimination have decreased over the recent decades[9], racial discrimination in labour markets remains stubbornly persistent[10,11]. In this Article, we examine a closely related but much less studied economic phenomenon—consumer discrimination against businesses, especially small businesses associated with Asian Americans, during the COVID-19 pandemic.

Historically, marginalized groups have responded to the challenges of labour discrimination by starting their own businesses providing unique goods and services. Many Asian immigrants to the United States achieved economic success using this model by starting businesses such as laundromats and ethnic restaurants[12]. In the late nineteenth century, the United States heavily encouraged Asian immigration to supply cheap labour for manufacturing their burgeoning railroad system[13]. These immigrants founded America's first Chinese restaurants. By the early twentieth century, both hostility towards Chinese immigrants and Americans' appetite for Americanized Chinese food had increased substantially[12]. The 1970s saw a further resurgence of American interest in 'authentic' Chinese food[12]. Although restaurant entrepreneurship remains a pathway to economic success for Asian Americans, discrimination by consumers can negatively impact the efficacy of this pathway, especially during periods of heightened anti-Asian sentiment.

Marginalization, stigmatization and even violence towards minority groups has been a frequent historical response to public health[14], terrorism[15] and economic[16] events. Although public blame (that is, rhetoric from politicians and mainstream media) is typically directed towards a singular foreign group, domestic hate crimes in response to these events often scapegoat American minorities and related groups that are mistakenly targeted. Tragically, Balbir Singh Sodhi, a Sikh American, was murdered after being mistaken for Arab Muslim in the aftermath of the 9/11 attacks, and Vincent Jen Chin, a Chinese American, was murdered after being mistaken for Japanese amidst rising blue-collar

[1]Marketing, University of Michigan, Ann Arbor, MI, US. [2]Political Science, Boston College, Boston, MA, US. [3]Microsoft Research, New York City, NY, US. [4]Management and Organizations, University of Michigan, Ann Arbor, MI, US. e-mail: huangjt@umich.edu; krupenki@bc.edu; David@ResearchDMR.com; profjlee@umich.edu

unemployment and American–Japanese economic competition in the early 1980s. Research on out-group homogeneity bias[17] suggested that people tend to view out-group members as more similar to one another, as opposed to in-group members. Adding to this bias, scholars have identified a cross-race effect—the tendency to recognize faces that belong to one's own racial group while having difficulty differentiating members of the cross-racial group[18,19]. Furthermore, individuals with less cross-race exposure are more likely to have prejudicial attitudes towards other groups[20,21]. Finally, Asian Americans have historically been subject to the perpetual foreigner stereotype—the perception that naturalized or even native-born Americans of Asian descent are foreign or un-American[22–24]. Taken together, these effects can allow prejudicial attitudes towards an out-group (Chinese, in our case) to drive prejudicial actions directed towards US domestic minority groups such as Asian Americans.

Here we examine the role of consumer discrimination against Asian businesses in the United States in the context of the COVID-19 pandemic. Previous studies have found that consumer discrimination substantially decreases small-business ownership and self-employment among people of colour in the United States[25–28], as does discrimination by funding sources[29]. Among small businesses, consumer discrimination is especially salient for restaurants that specialize in ethnic cuisines, as the food's ethnic origin is a key aspect of product differentiation. Although restaurant entrepreneurship remains a pathway to economic success for Asian Americans, discrimination by consumers can negatively affect the efficacy of this pathway, especially during periods of heightened anti-Asian sentiment. We leverage the COVID-19 pandemic as an exogenous shock to rhetoric and attitudes about Asian Americans in the United States. Soon after COVID-19 began spreading in the United States, then-President Trump and the Republican Party began a concerted effort to blame China for the virus. Political and media figures used the phrases 'China virus' and 'Kung Flu' to describe the coronavirus, in contradiction to World Health Organization (WHO) guidance[30] and previous research demonstrating how disease naming can lead to stigmatization, particularly of marginalized and minority groups[14,31,32]. The effects of this rhetoric did not go unnoticed—the number of anti-Asian hate crimes spiked during the pandemic[33,34], impacting both Chinese Americans and the broader Asian American community. Self-reports[35,36] and surveys[37] from Asian American citizens and business owners have suggested that the community has seen disproportionate, negative impacts during the pandemic.

Innuendos of 'uncleanness' and disease have long been used to stigmatize marginalized populations and justify their expulsion. From blaming European Jews for the bubonic plague in the Middle Ages[38] to claiming that immigrants crossing the southern border of the United States are 'diseased'[39], majority groups have long misattributed blame for diseases to 'undesirable' minority populations. In the United States, the portrayal of immigrants as dangerous and diseased shaped immigration policy for decades[40,41]. Modern-day attitudes towards disease threat are closely related to anti-immigration attitudes[42,43]. This carries forward into the present with rhetoric falsely trying to tie the fourth wave of COVID-19 illness to undocumented immigrants coming through the US southern border[44].

These stigmas have been especially prevalent in the treatment of Asian Americans in the nineteenth and twentieth centuries. Medical examinations of Chinese immigrants arriving at Angel Island were frequently harsher than those of Europeans at Ellis Island, and the rejection rate for Chinese immigrants was at least five times higher than for European immigrants at Ellis island[41]. These attitudes extended towards Asian cultural products in the United States, especially Chinese food. Although early Chinese restaurants founded in San Francisco during the California Gold Rush were praised as tasty and economical, the rising tide of Sinophobia soon led to rumours of the consumption of rats and snakes as Chinese delicacies, leading to a decrease in the popularity of Chinese restaurants[12]. More recently, the popularization of the term 'Chinese restaurant syndrome', based in medically unfounded fears over the effects of monosodium glutamate[45,46], is another example of cultural discrimination against Chinese restaurants.

Portrayals of the COVID-19 crisis echoed many of these historical patterns of negative attitudes and discrimination against this group in the face of public health concerns. The SARS-CoV-2 virus was regularly referred to as the 'Chinese virus' or 'China virus', both offline[47] and online[48–50]. Donald Trump and Trump-supporting Republicans and media began to refer to COVID-19 as the 'China virus' and explicitly blame the pandemic on China despite consistent criticism from Asian Americans and left-leaning media outlets. Between 16 March 2020 and 3 Jan 2021, Trump used the phrase 'China virus' or 'Chinese virus' in 54 separate tweets. This explicit blame on China by the politicians was then reinforced and further spread into the mainstream media outlets that rebroadcast this rhetoric. Recent research has demonstrated how social media also has a vital role in building and reproducing negative sentiment against marginalized groups. For example, recent studies have examined the spread of anti-Muslim sentiment through hashtags on Twitter[51,52]. Similarly, two studies to date have demonstrated the link between hashtags that used the language of this rhetoric (for example, #Chinesevirus) and anti-Asian sentiments on Twitter[50,53]. Although establishing a causal relationship between the political rhetoric and anti-Asian sentiment is beyond the scope of our current research, this suggests the possibility that anti-Asian sentiment initiated by the political figures may have spread broadly and quickly on both mainstream media and social media.

Against this backdrop, recent research adds to the growing evidence that Asian Americans were blamed for the COVID-19 pandemic. For example, fear of COVID-19 is highly correlated with anti-Asian attitudes and support for anti-Asian immigration policies in the United States[54]. Furthermore, an experimental study has shown that emphasizing the origin of COVID-19 to China increased anti-Asian sentiment and xenophobia[55]. Following this logic, we argue that the COVID-19 pandemic served as an exogenous shock—an unpredictable event from outside the economic system, such as a war, natural disaster, global pandemic or new technology, that affects economic behaviour—that gave voice to politicians who were increasingly making explicitly racial appeals by singling out marginalized groups[56], thereby contributing to the increase in anti-Asian attitudes within the United States.

Drawing from the psychological theory of blame, we put forth the idea that, not only was the country of origin directly blamed for the pandemic, but also other groups that are often mislabelled as Chinese subsequently became the targets of collective blame. Alicke's model of culpable control[57] suggests that blame is the outcome of psychological processes driven by cognitive and motivational biases, which may be independent of a party's actual liability[57–59]. Furthermore, his theory posits that people may assign blame on the basis of the proximity criteria. To the extent that the associated party is viewed as sufficiently proximate to the party that is presumed to be guilty, it is possible that even the group (that is, businesses owned by Chinese Americans) that is not blamed for the harm may still be cognitively implicated. Although there were legitimate questions about whether or not food could carry COVID-19 in the early days of the pandemic, this concern alone would not be sufficient if some restaurants were disproportionately affected by the COVID-19 pandemic compared with others, as there was not a legitimate concern about any particular type of food. Facing COVID-19 as an exogenous shock and the anti-Asian rhetoric and attitudes that followed, we hypothesize the following.

H1: during the COVID-19 crisis, Chinese restaurants will see a substantial decrease in visits relative to non-Asian restaurants. Much of the consumer research on blame spillover has been documented in the context of brands that were implicated in moral transgressions. This effect was found to be more prominent to the brands that consumers identify as similar to the brand that was implicated in ethical scandal[60–62]. On the basis of this literature, we further argue that how consumers ascribe blame on the associated groups may contribute to the struggles of

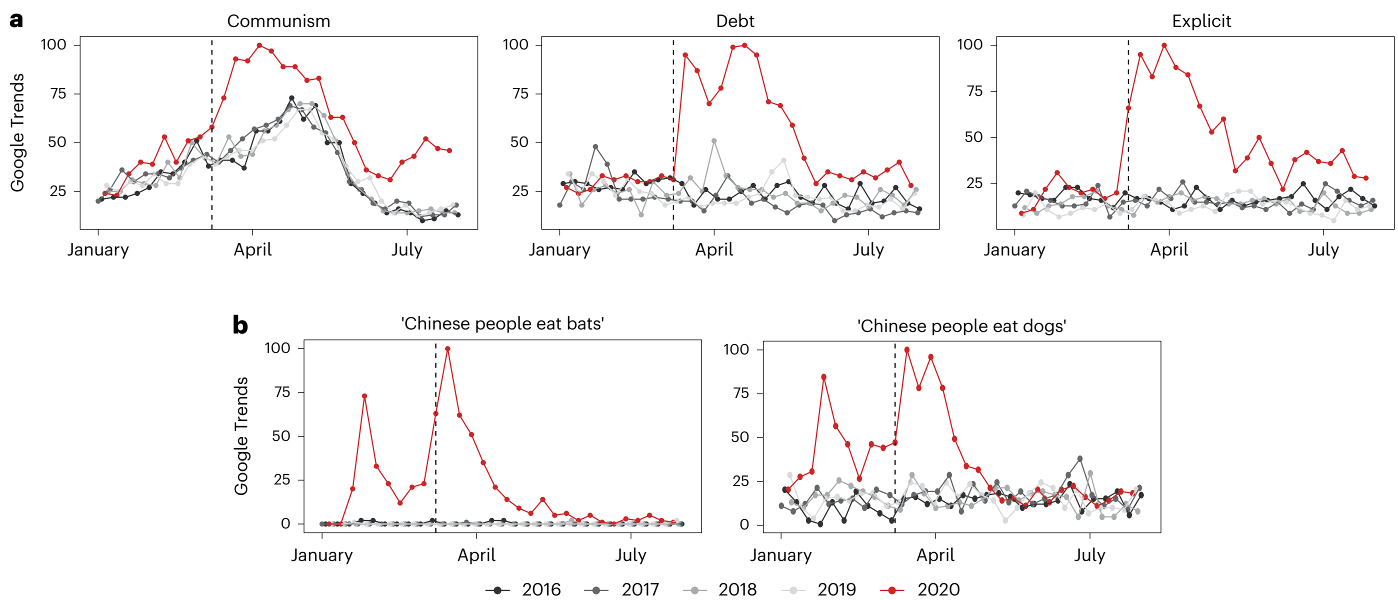

Fig. 1 | China-related searches. a, Google Trends shows sharp increases in negative searches relating to China during the week of 11 March 2020. The vertical dashed line represents the Declaration of National Emergency issued by former US President Donald Trump on 13 March 2020. There were no similar increases in these searches during the same time period in 2016–2019. **b**, Google Trends shows sharp increases in searches relating to Chinese people eating bats and dogs during the week of 11 March 2020. There were no similar increases in these searches during the same time period in 2016–2019. There is a substantial correlation between searches for eating bats and eating dogs, despite the fact that the dog-eating stereotype has no relevance to the COVID-19 pandemic.

other Asian restaurants that are not Chinese. This blame spillover may occur through two channels. First, it is possible that non-Chinese entities were incorrectly identified as Chinese, thereby being erroneously blamed for the pandemic. Second, it is also plausible that non-Chinese entities were correctly identified (which we call the 'ethnic misidentification hypothesis', described below), but viewed as a proximate entity under the broader umbrella of Asian race and ethnicity, thereby being categorically avoided. Both possibilities support the idea that other Asian restaurants will be negatively affected at the early onset of COVID-19 in the United States, leading to our second hypothesis:

H2: after COVID-19, non-Chinese Asian restaurants will also experience a substantial drop in visits relative to non-Asian restaurants. Notably, these portrayals were not spread evenly across the population—Republican-leaning news outlets, such as Fox News, were more likely to blame China for the pandemic compared with other outlets[63]. Owing to the prevalence of these narratives among Republican politicians and news sources, we argue that this shock was not homogeneously distributed throughout the population. Scholars have long noted that partisans in the United States tend to follow opinion cues provided by leaders of their political party[64–66]. Partisans are much more likely to follow suggestions and absorb information when it is presented to them by leaders in their own party, as compared to non-partisan figures and especially figures from the opposing party. This partisan-cuing effect extends to a variety of topics, including vaccination[67], mask wearing[68] and COVID-19 blame attribution[69]. This suggests that Republicans, whose party leaders and media outlets engaged in anti-Asian-cuing behaviour, should be more likely to respond with consumer discrimination against Chinese and Asian restaurants, leading to hypothesis 3.

H3: areas with greater support for Trump would see a larger relative decrease in visits to Chinese restaurants compared with areas with lower support for Trump. Finally, we propose a potential mechanism for spillovers to non-Chinese Asian restaurants (such as 'Tiger Belly Noodle Bar') of which the names are ethnically ambiguous but could potentially be classified as Chinese. During the pandemic, anti-China rhetoric often invoked prejudice and stereotypes such as the eating of bats or snakes[70] and martial arts[71], which, while targeted at China, are common stereotypes of East Asians as a whole. Politicians' use of these stereotypes could both activate in-group favouritism and be indicative of the prevalence of these out-group stereotypes among their constituents. In either case, an activation of group membership has been shown to change how individuals process and perceive information about the out-group members, with the potential to increase perceived out-group homogeneity[72–74]. We therefore predict that Trump voters who are more exposed to anti-China rhetoric from Republican-leaning news outlets will exhibit decreased differentiation between Asian ethnic groups and thereby increased chances of misidentification. This yields our final hypothesis.

H4: Trump voters would be more likely to misidentify non-Chinese Asian restaurants compared with non-Trump voters. We present empirical results that test these hypotheses within consumer mobility data by comparing pre- and post-pandemic consumption behaviour, supplementing our analysis with search data and a series of surveys to describe linkages between political rhetoric, consumer sentiment, search and subsequent consumer traffic behaviour (Methods). We found clear evidence of sharp attitudinal shifts against China, Chinese Americans and Asian Americans as a whole during the COVID-19 pandemic. These shifts have the potential to create economic harm for Asian American communities, as people who have internalized this rhetoric look to avoid products affiliated or associated with China. Furthermore, Americans tend to stereotype Asian Americans as foreign, consistently overestimate the fraction of Asian Americans who are ethnically Chinese, and have difficulty differentiating between Chinese Americans and other Asian Americans, putting the broad Asian American community at risk from anti-Chinese sentiment and behaviour. Consistent with our hypotheses, we document and quantify the disproportionate decrease in business for both Chinese and other non-Chinese Asian restaurants during the COVID-19 crisis, suggesting that the increase in anti-China sentiment incurred not only a social cost, but also a real economic cost to the Asian American community.

Results

Using web search, survey and movement data, we documented and quantified the impact of anti-China sentiment on both Chinese Americans and the spillover effects on other Asian American populations.

 https://doi.org/10.1038/s41562-022-01493-6

Table 1 | Effects of the pandemic on Asian restaurant traffic

	Dependent variable: log-transformed visits			
	Model 1	**Model 2**	**Model 3**	**Model 4**
Is Asian×post-COVID	−0.203			
s.e.	0.015			
P	<0.001			
95% CI	−0.232 to −0.174			
Is Chinese×post-COVID		−0.115		−0.115
s.e.		0.014		0.014
P		<0.001		<0.001
95% CI		−0.142 to −0.088		−0.142 to −0.088
Is non-Chinese Asian×post-COVID			−0.288	−0.288
s.e.			0.020	0.020
P			<0.001	<0.001
95% CI			−0.327 to −0.249	−0.327 to −0.249
Case rate	−7.224	−7.500	−7.703	−7.296
s.e.	1.383	1.395	1.455	1.397
P	<0.001	<0.001	<0.001	<0.001
95% CI	−9.935 to −4.513	−10.234 to −4.766	−10.555 to −4.851	−10.0341 to −4.558
Week fixed effects	Yes	Yes	Yes	Yes
Restaurant fixed effects	Yes	Yes	Yes	Yes
Observations	11,086,220	10,256,567	10,294,852	11,086,220
R^2	0.837	0.837	0.837	0.837
Adjusted R^2	0.831	0.832	0.832	0.831
Residual s.e.	0.448 (d.f. = 10,728,568)	0.448 (d.f. = 9,925,678)	0.449 (d.f. = 9,962,728)	0.448 (d.f. = 10,728,567)

The results of a difference-in-difference regression examining the relative decrease in traffic for Asian versus non-Asian restaurants in the post-pandemic period. Week and restaurant fixed effects were used to account for parallel time trends and group membership, respectively. Robust standard errors are clustered at the week and restaurant level and are displayed below each coefficient estimate. Model 4 uses the same unrestricted dataset as model 1, breaking the 'is Asian×post-COVID' interaction into two separate interaction terms for Chinese and non-Chinese Asian restaurants in the post-pandemic period. Models 2 and 3 exclude non-Chinese Asian and Chinese restaurants, respectively, to ensure that the comparison group is always non-Asian restaurants. The results show a significant decrease in traffic for Asian, Chinese or non-Chinese Asian restaurants during the post-pandemic period compared with non-Asian restaurants.

First, we used web search data to demonstrate the exogenous shock of the COVID-19 pandemic on American conceptions of China and Chinese food. Next, movement data enabled us to measure the effect of anti-Asian attitudinal shifts on consumer discrimination against both Chinese and other Asian restaurants, quantifying the economic effect of anti-Chinese rhetoric on Asian American communities. Finally, we used survey data to examine different underlying mechanisms that may influence these shifts.

Web searches confirm a pandemic spike in anti-Chinese sentiment

Our analysis first established the temporal relationship between the COVID-19 pandemic and anti-Asian attitudes. We expect that searches that tie COVID-19 to China would spike during the pandemic (that is, a search for 'China virus' would not necessarily tell us anything about the searcher's attitudes), whereas searches for something like 'China owns us' would be more indicative of anti-Asian attitudes, as they have no clear relationship to the pandemic. Confirming this, all three categories of non-COVID-related anti-China searches (that is, searches relating to China and Communism (political), searches relating to China and debt (economic), and searches relating to explicit anti-China phrases (social/stereotypical)) are related to negative attitudes towards China and stereotypes about Chinese people and culture that predate the pandemic (Fig. 1a). Our results suggest that search patterns in 2020 looked very different from those in the four previous years. In the case of Communism searches, we saw a slightly subtler effect, whereby the overall number of searches for China and Communism was substantially higher throughout the year, beginning in mid-March. For searches around debt and explicit anti-China searches, we saw a sharp discontinuity at the week of 11 March 2020 that was not present in any of the previous years, despite the United States starting a well-covered trade war with China in 2019.

Specifically, we also compared searches for Chinese consumption of bats versus consumption of dogs. Search interest in Chinese bat consumption was probably driven by media coverage, but consumption of dogs has no relationship to the pandemic and did not receive media coverage. As such, if we see an increase in searches for Chinese consumption of dogs, this is another possible indicator of affirming the negative stereotypes about China. Searches related to eating animals, presented in Fig. 1b, further underscore these results. Although there were clear, news-driven spikes for eating bats around the emergence of COVID-19 and again at the beginning of the pandemic in the United States, the relationship between searches for eating bats and eating dogs is very clear and distinct. Dog-eating behaviour had no relationship to the pandemic, but is closely related to anti-Chinese stereotypes. These search patterns show a sharp discontinuity in anti-Chinese sentiment during the COVID-19 pandemic. Next, we consider the impacts of this shift in sentiment on the livelihoods of Asian Americans in the United States.

Consumers avoid Asian restaurants during the pandemic

An analysis of consumer mobile device location data using a difference-in-difference framework indicates that consumers exhibited

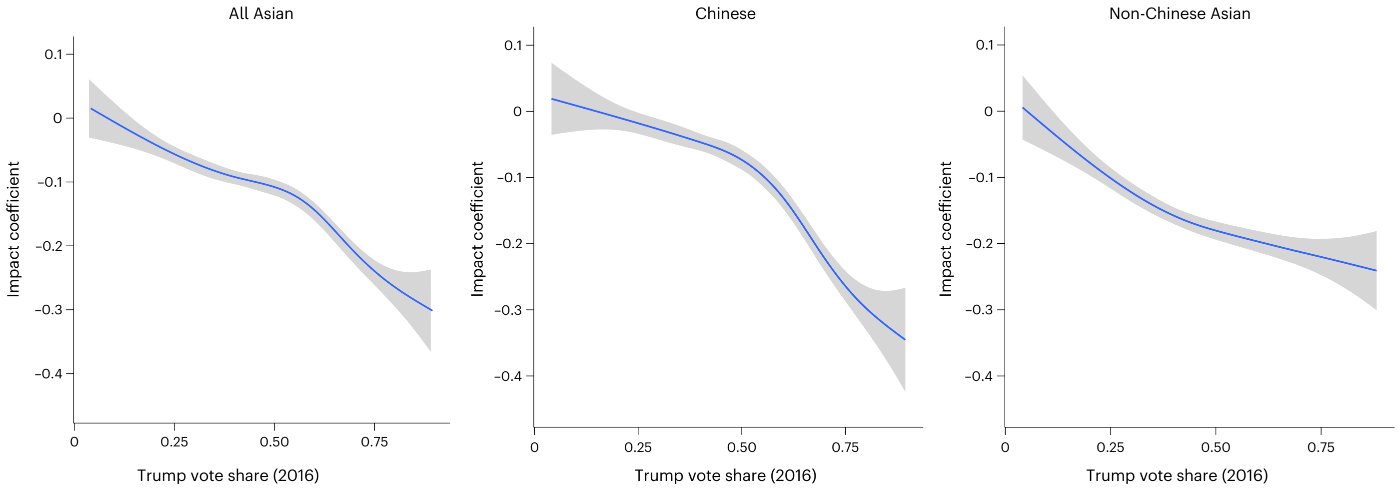

Fig. 2 | ZIP-code-level heterogeneity in Asian restaurant avoidance by Trump vote share. ZIP-code-level impact to Asian, Chinese and non-Chinese Asian restaurants by Trump vote share in 2016. Impact coefficients were calculated for each ZIP code using the difference-in-difference method using the specification in equation (1) relative to non-Asian restaurants within the ZIP code. The grey shaded region displays the 95% CI of the mean impact coefficient (blue line) of ZIP codes with the given level of Trump support, visualized using LOESS smoothing with span = 0.5. These plots indicate that the Trump vote share in 2016 correlates with greater avoidance of Asian, Chinese and non-Chinese Asian restaurants in the post-pandemic period.

relative avoidance of Asian restaurants (Table 1). We found that, during the period after the onset of COVID-19, Asian restaurant traffic decreased by a substantial 18.4% (two-sided t-test, $P < 0.001$, 95% confidence interval (CI) = −15.9% to −20.8%) relative to non-Asian restaurant traffic during the same period and after controlling for COVID-19 case rates. Chinese restaurant traffic dropped 10.9% (two-sided t-test, $P < 0.001$, 95% CI = −8.4% to −13.3%), whereas non-Chinese Asian restaurant traffic saw a greater (two-sided Z-test for comparison of regression coefficients, $P < 0.001$, 95% CI = 12.6% to 22.0%) decrease of 25.0% (two-sided t-test $P < 0.001$, 95% CI = −22.1% to −27.9%). These patterns support hypotheses 1 and 2, which predicted that both Chinese and non-Chinese Asian restaurants would experience substantial decreases in visits relative to other types of restaurants. The decrease in traffic represents a considerable loss of revenue for Asian restaurants, which we estimate through a combination of counterfactual simulation and a back-of-the-envelope calculation. Our calculation indicates that the relative consumer avoidance of Asian restaurants through the pandemic cost those restaurants US$7.42 billion in foregone revenue in 2020.

Greater Trump support is associated with a larger drop in Asian restaurant traffic

Given that former President Trump was a main source of anti-China rhetoric assigning pandemic blame to China, we look at whether greater support for Trump was associated with a larger relative drop in Chinese and, more broadly, Asian restaurant traffic in the post-pandemic period (hypothesis 3). For this analysis, we use Trump's 2016 vote share rather than his 2020 vote share, as his share in 2020 may have been affected by both regional variation in pandemic severity and perceptions of his management of the pandemic. As additional robustness, we also replicate these results using the 2018 election data (Supplementary Information). We examined heterogeneity in Asian restaurant avoidance by repeating our main analysis at the ZIP-code level, calculating our difference-in-difference estimation of pandemic traffic impacts for (1) all Asian restaurants; (2) Chinese restaurants; and (3) non-Chinese Asian restaurants; the results are visualized in Fig. 2, and interaction regression results are reported in Table 2. The ZIP-code-level subsamples replicate our main effects, indicating persistent negative traffic impacts on Asian restaurants during the pandemic. Furthermore, there is a visible negative correlation between traffic impact and Trump's 2016 vote share at the ZIP-code level (Fig. 2). This visual pattern was confirmed by a regression test: Trump's 2016 vote share is a significant predictor of negative traffic impact (consumer avoidance) for each of Asian (two-sided t-test, $P < 0.001$, 95% CI = −0.036 to −0.080), Chinese (two-sided t-test, $P < 0.001$, 95% CI = −0.027 to −0.075) and non-Chinese Asian (two-sided t-test, $P < 0.001$, 95% CI = −0.056 to −0.110) restaurants as shown in Table 2, which regresses the coefficient of avoidance at the ZIP-code level on each ZIP code's voting share in 2016. Finally, while the average coefficients estimated in Table 1 showed greater avoidance of non-Chinese Asian restaurants compared with Chinese restaurants, we observe in Fig. 2 that this trend reverses for ZIP codes with high Trump support. This provides support for hypothesis 3—that greater Trump support would be associated with greater avoidance of Chinese restaurants.

Evidence for consumer discrimination

Consumers blame pandemic spread on Asians and express fear of Chinese food. We assessed consumer blame for pandemic spread by asking American respondents a straightforward question: 'Which racial or ethnic group do you believe is most responsible for bringing COVID-19 (also known as coronavirus) into the US (if any)?' This survey on consumer blame was run in four waves throughout the pandemic, and, for the first three waves, we had one iteration of the question with six possible answers presented in a randomized order: 'Asians', 'Blacks', 'Latinos', 'Whites', 'No racial or ethnic group is responsible' and 'Don't know'. We would expect that, if anything, social desirability would motivate people to over-respond 'no racial or ethnic group is responsible', but that answer hovers in the low 60s, with a meaningful (but monotonically decreasing) 27% (wave 1) to 17% (wave 4) reporting that Asians, the most commonly blamed ethnic group, are the most responsible for pandemic spread. In wave 4 on 15 April 2021, we randomly assigned half of the sample to see a different set of answers to the same question, again in a randomized order: 'Chinese', 'Japanese', 'Italian', 'French', 'Mexican', 'Greek', 'Indian', 'Thai', 'other', 'no racial or ethnic group is responsible' and 'don't know'. Even at this late date, 38% answered that Chinese people are the most responsible for pandemic spread. Although 'no racial or ethnic group is responsible' was the most popular answer under all of the answer sets and days, a non-negligible number of Americans blame Asian, and Chinese in-particular, individuals for bringing COVID-19 into the United States. These results are visualized in Fig. 3a.

https://doi.org/10.1038/s41562-022-01493-6

Table 2 | Heterogeneity in effects

	Dependent variable: traffic impact to restaurant type		
	Asian	Chinese	Non-Chinese Asian
Trump 2016 vote share	−0.058	−0.051	−0.083
s.e.	0.011	0.012	0.014
P	<0.001	<0.001	<0.001
95% CI	−0.080 to −0.036	−0.075 to −0.027	−0.110 to −0.0556
Constant	−0.027	−0.029	−0.011
s.e.	0.005	0.006	0.007
P	<0.001	<0.001	0.116
95% CI	0.017–0.037	−0.041 to −0.017	−0.025 to −0.003
Controls			
Median household income	Yes	Yes	Yes
College education	Yes	Yes	Yes
Percentage population white	Yes	Yes	Yes
Percentage population Asian	Yes	Yes	Yes
Observations	11,773	10,910	7,723
R^2	0.002	0.002	0.004
Adjusted R^2	0.002	0.002	0.004
Residual s.e.	0.200 (d.f.=11,771)	0.208 (d.f.=10,908)	0.204 (d.f.=7,721)
F statistic	28.766 (d.f.=1; 11,771)	19.083 (d.f.=1; 10,908)	34.523 (d.f.=1; 7,721)

The heterogeneity in relative impacts to Asian, Chinese and non-Chinese Asian restaurants is shown. Impact coefficients were calculated for each ZIP code by difference-in-difference through the specification in Table 1 relative to non-Asian restaurants within the ZIP code and then regressed on Trump's 2016 vote share within the ZIP code, controlling for median household income, college education and racial demographics within each ZIP code. Robust s.e. values are reported below each coefficient estimate. The coefficient on Trump's 2016 vote share is negative and significant in each case, reinforcing the correlation between Trump support and avoidance of Asian restaurants shown in Fig. 2.

Trump voters blamed Asians, in particular Chinese, at much higher rates compared with Biden voters for the spread of the pandemic. In the final survey on 15 April 2021, just 12% of Biden voters said that they blame Asian people, with 32% blaming Chinese people (Fig. 3a). However, in the same survey, 27% of Trump voters blamed Asian people (mean difference, +14 percentage points (pp) versus Biden voters, two-sided *Z*-test, $P < 0.001$, 95% CI = +4.4 pp to +23.8 pp), and a majority (56%), blamed Chinese people (mean difference +24 pp versus Biden voters, two-sided *Z*-test, $P < 0.001$, 95% CI = +14.2 pp to +33.7 pp).

We also asked a direct question about fear and risk of contracting COVID-19: 'When considering delivery food, ordering which (if any) of the following types of food do you believe presents an increased risk of contracting COVID-19 (also known as coronavirus) into the US (if any)?' This question allowed for multiple answers, and 'Chinese food' was very consistently the leading answer with between 15% and 22% (Fig. 3b). This was between 5 and 9 pp higher than the next answer. Notably, Biden and Trump voters exhibited a small gap in response to this fear question (22% versus 25%, respectively), whereas our restaurant-traffic analysis indicated that avoidance of Chinese and more broadly Asian restaurants is strongly and significantly correlated with support for Trump. This suggests that blame sentiment may have had a larger role in restaurant avoidance than fear of contracting COVID-19 from Chinese food.

Finally, we examined the interaction between perceptions of Asian homogeneity and directed blame or fear, as shown in Fig. 4. We asked respondents 'What fraction of Asians in the US do you think are ethnically Chinese?' We noted two trends: first, respondents consistently overestimated the fraction of Asians Americans who are Chinese (mean survey response, 35% versus 24% actual[75]). This is consistent with the predictions of out-group homogeneity bias, whereby respondents will tend to overestimate the homogeneity of the out-group. Second, examining respondents who believed that a majority (50% or more) of Asians in the United States were ethnically Chinese, we found that this group is also significantly more likely to believe that Chinese food represented an increased risk of contracting COVID-19 (27% versus 16% among respondents who did not think the majority of Asians are ethnically Chinese; mean difference, +11 pp, two-sided *Z*-test, $P < 0.001$, 95% CI = +7.0 pp to +14.9 pp) or that Asians were to blame for the spread of COVID-19 (28% versus 23% among respondents who did not think that the majority of Asians are ethnically Chinese; mean difference, +5 pp, $P = 0.020$, 95% CI = +0.0 pp to +9.6 pp). This second trend supports the relationship between the perceived homogeneity of Asians as a group and fear and blame directed towards Asian American individuals.

Searches relating to Chinese food safety increased. To further investigate the question of fear versus discrimination, we examined the search patterns around Chinese restaurants and other restaurants from 2016 to 2020. Figure 5 shows that searchers exhibited very different search patterns around Chinese restaurants. For regular searches around restaurant safety, we see a large spike in the week immediately after Trump's 11 March 2020 address. However, for searches relating to the safety of Chinese food, the largest spikes came in February and early March 2020, with the largest spike during the week of 11 March 2020. These results again support hypothesis 1 and show that people were thinking about the safety of Chinese restaurants and other restaurants differently during the pandemic.

Misidentification as a spillover mechanism into non-Chinese Asian restaurants. Following on from our mobility analysis, we investigated the potential for anti-China messaging spillovers to create a decrease in business for non-Chinese Asian restaurants. We specifically examined confusion among Asian restaurants as a potential mechanism, motivated by extant literature on out-group homogeneity bias and a history of attacks against Asian Americans in cases in which attackers were motivated by hatred against one Asian group yet attacked victims of another Asian group[76,77]. In a separate survey with 2,345 participants, each participant was shown a list of 20 ethnic restaurant names (selected from Chinese, Japanese, Korean, Thai, Vietnamese, Indian, Mexican, Italian and French), randomly selected from real, mono-ethnic restaurants within the SafeGraph location dataset, and we asked the participants to categorize each one by its ethnicity. We found that misidentification is high: 33% of Asian restaurants are incorrectly labelled by respondents. The most commonly mislabelled Asian restaurants were Korean and Vietnamese, which were incorrectly labelled 52% and 47% of the time, respectively. Both of these were most commonly mislabelled as being Chinese, consistent with a misclassification mechanism behind Asian restaurant avoidance.

We also broke down the correct response rate by participants' 2016 and 2020 voting preferences, as shown in Fig. 6. These results indicate that Trump 2016 and 2020 voters were more likely to misidentify Asian restaurants (36.4% and 35.2% misidentification, respectively) compared with Clinton 2016 and Biden 2020 voters (30.9% and 31.6% misidentification, respectively). Two-sided *Z*-tests for a difference in proportions comparing Trump versus Clinton voters in 2016 and Trump versus Biden voters in 2020 indicate that these differences in misidentification rate are highly significant ($P < 0.001$ for each), supporting hypothesis 4.

https://doi.org/10.1038/s41562-022-01493-6

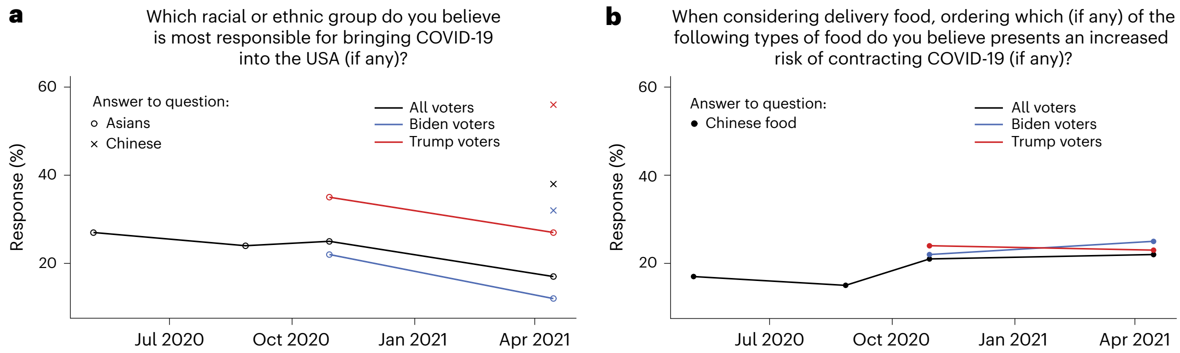

Fig. 3 | Survey on COVID-19 blame and fear of Chinese food. **a**,**b**, The survey participants were asked the indicated questions on blame (**a**) and fear (**b**). For **a**, when the answer was 'Asians', the full set of other options included: 'Blacks', 'Latinos', 'Whites', 'No racial or ethnic group is responsible' and 'Don't know'. When the answer was 'Chinese' the full set of other options included: 'Japanese', 'Italian', 'French', 'Mexican', 'Greek', 'Indian', 'Thai', 'Other', 'no racial or ethnic group is responsible' and 'don't know'. The four waves have the following raw demographics—wave 1, 5 May 2020 (57% female; mean age, 43 years; age s.d. 16 years); wave 2, 27 August 2020 (55% female; mean age, 42 years; age s.d., 15 years); wave 3, 29 October 2020 (57% female; mean age, 38 years; age s.d., 13 years); wave 4, 15 April 2021 (49% female; mean age, 39 years; age s.d., 11 years)—but were raked to represent US demographics.

Discussion

Our results support the role that the COVID-19 pandemic had in activating latent anti-Asian sentiment as expressed through consumer search, survey responses and foot-traffic behaviour. We found empirical support for each of our hypotheses, namely that both Chinese and non-Chinese Asian restaurants saw a drop in traffic during the pandemic, that areas with more Trump support saw a larger relative drop in Chinese restaurant traffic than those with lower Trump support, and that Trump voters were more likely to misidentify Asian restaurants compared with non-Trump voters.

A natural question that may arise from our analysis is the extent to which the observed changes in traffic may be driven by supply-side changes such as Asian restaurants independently deciding to limit operations versus demand-side changes such as consumer avoidance of Asian businesses. Although we cannot directly quantify this, we provide evidence that a mechanism by which our observed drop in traffic is purely driven by a reduction in Asian restaurant operations is improbable. Small business owners look to garner revenue to support themselves, their employees and cover fixed expenses such as rent, suggesting that a greater reduction in Asian restaurant operations relative to comparable non-Asian restaurants in the absence of changes in Asian restaurant demand would result in unnecessary economic losses for Asian restaurant owners. Other interviews and anecdotal reports[78] from Asian American business owners also support that lack of demand is a key impediment. Furthermore, as illustrated in the survey analysis, a sizable fraction of consumers expressed blame towards Asians for pandemic spread and fear that consuming even takeaway Chinese food would present an increased risk of contracting COVID-19, reinforcing the major role of the shifting consumer demand for Asian food. A deeper examination of this question on the relative roles of supply and demand side explanations for the observed empirical patterns is a promising area for future research, although it is outside the scope of this study, which focuses on first quantifying the economic effects of the COVID-19 pandemic and the associated stigmatization on Asian American restaurants and the corresponding communities. Stigmatization and pandemic blame are underlying driving factors under both supply- and demand-side mechanisms that impact the economic livelihoods of Asian Americans.

Our finding that Chinese restaurant avoidance increased with Trump vote share suggests that the assignment of pandemic blame had downstream impacts on consumers' food-consumption choices. As a substantial fraction of Asian restaurants in the United States serve Chinese food, the finding that Asian restaurants as an average, overall group saw a decrease in traffic is unsurprising. What is less expected is that non-Chinese Asian restaurants saw a greater average decrease in traffic compared with Chinese restaurants at the nationwide level. In understanding this heterogeneity in effects between Chinese and non-Chinese Asian restaurants, we again look to Fig. 2 and observe that ZIP codes with very low levels of Trump support have less of a negative impact in traffic to Chinese restaurants relative to non-Asian restaurants in similar locations. Furthermore, the same figure shows that avoidance of Chinese restaurants is more sensitive to Trump support than avoidance of non-Chinese Asian restaurants. This is explored further and reinforced by the results of the three-way interaction model in the Supplementary Information. This probably reflects how anti-Chinese sentiment became politically polarized during the pandemic. Although former president Trump had used stigmatized language to refer to the pandemic, his political opponents such as then Speaker of the House Nancy Pelosi made efforts to explicitly support Chinatowns through the pandemic[79]. We also must recognize the community efforts of Asian American organizations, such as Welcome to Chinatown, Send Chinatown Love and Think!Chinatown, among many more through the pandemic to support Chinatowns, Chinese American restaurants and Asian American businesses more broadly. Moreover, mainstream press coverage[78,80–83] tended to focus on how

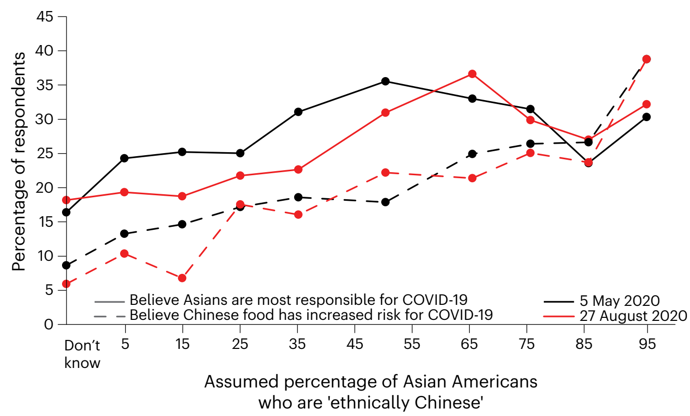

Fig. 4 | Fear, blame and ethnicity perceptions of Asian Americans. Responses to questions on fear and blame broken down by the perceived percentage of Asian Americans who are ethnically Chinese from waves 1 and 2 of the survey (5 May 2020 and 27 August 2020, respectively). Respondents who perceive that more Asian Americans are Chinese were also more likely to blame Asians for the spread of COVID-19 in the United States and believed that Chinese food posed an increased risk of contracting COVID-19.

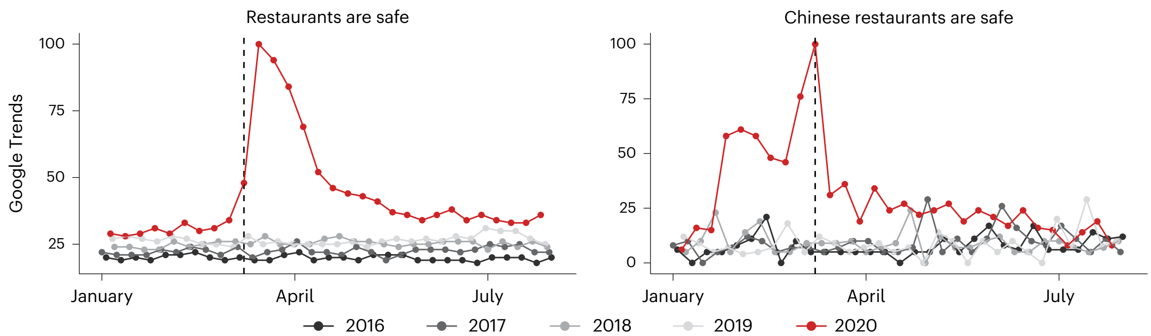

Fig. 5 | Food safety searches. The vertical dashed line represents the Declaration of National Emergency issued by former US President Donald Trump on 13 March 2020. Google Trends data show that searches relating to concern about the safety of Chinese food peaked earlier compared with searches relating to concerns about the safety of restaurants in general.

Chinese American businesses and Chinatowns struggled through the pandemic, which, in combination with the community support organizations described, probably led sympathetic consumers to specifically identify and support Chinese restaurants during this period. Asian American advocacy groups and efforts tend to be centred around urban areas and more liberal-leaning population centres, which shows up in our data as lower avoidance in areas with low Trump support and affects our observed patterns on average avoidance of Chinese versus non-Chinese Asian restaurants nationwide.

By contrast, we observed an inflection point when Trump support crosses around 65% and avoidance of Chinese restaurants is greater than avoidance of non-Chinese Asian restaurants. This is consistent with our survey results in the previous section, which indicate correlations between political affiliation, pandemic blame towards Asian Americans, increased perceptions of risk from Chinese and Japanese food, and indications of outgroup homogeneity (such as overestimating the proportion of Asian Americans that are Chinese). In the locations in which our surveys predict the greatest stigma against Asians, Asian Americans and Chinese food, we do see greater avoidance of Chinese restaurants compared with non-Chinese Asian restaurants, and these levels of avoidance are very high compared with comparable non-Asian restaurants in these areas. For these reasons, we believe that the patterns of observed heterogeneity reinforce rather than diminish the role of political racial stigma in driving restaurant consumption.

Recalling our other survey result in Fig. 4, we noted a significant interaction in that respondents who (falsely) believed that a majority of Asians in the United States were Chinese were also more likely to report a fear that Chinese food represented an increased risk of contracting COVID-19. We also found that greater Trump support is associated with both increased misclassification of Asian restaurants and greater avoidance of non-Chinese Asian restaurants (Fig. 2). Taken together, these results illustrate the linkage between expressions of out-group homogeneity bias (perceived increased homophily or inability to distinguish between out-groups) and Asian restaurant avoidance attitudes and behaviours. These patterns are all highly consistent with a mechanism whereby non-Chinese Asian restaurant avoidance is influenced by ethnic misidentification as stated in hypothesis 4. However, we caution that this does not constitute a causal test of the role of ethnic misidentification or enable us to disentangle the relative roles of misidentification and alternative mechanisms such as collective blame that are also correlated with out-group homogeneity.

Finally, a comparison of pandemic blame and food fear survey results suggests that food safety concerns were probably not the determining factor behind the disproportionate drop in visits for Chinese and non-Chinese Asian restaurants among Trump supporters. Trump voters were relatively comparable to Biden voters in expressing safety concerns with consumption of Chinese food (25% versus 21%, respectively), yet Trump voters were approximately twice as likely to attribute blame for pandemic spread to Asians (27% versus 12%) or Chinese (56% versus 32%).

In summary, the patterns that emerge are consistent with our theories on the role of collective blame and outgroup homogeneity in driving consumer avoidance of Chinese American restaurants and the spillovers to even non-Chinese Asian American restaurants. Here we highlight again that a majority (56%) of Trump voters in our 15 April 2021 survey blamed Chinese people for the spread of the pandemic and, in the between-participants design, approximately half as many Trump voters (27%) blamed Asians as a whole. At the time of the survey, COVID-19 cases had fallen considerably from their peak at the beginning of 2021, and yet blame levels remained comparatively robust. Survey respondents on average overestimated the fraction of Asian Americans who are ethnically Chinese, and individual respondents who greatly overestimated the fraction were also significantly more likely express that Asians were to blame for the pandemic or that Chinese food represented an increased risk of contracting COVID-19. The notion of collective blame holds that feelings of blame extend from individuals or subgroups to the collective whole, and that one's willingness to do so depends on the ability to see out-groups as a homogeneous, monolithic entity. The perception of division between in-group and out-group membership can both reinforce and be reinforced by stereotypes[84], as probably occurred through then-President Trump calling COVID-19 'Kung Flu', which tied elements of Chinese and more broadly Asian cultural heritage, persistent stereotypes of Asian Americans[85] and the chaotic beginnings of a global pandemic.

Contributions

Our contributions are three-fold. First, we examined the role of racially salient events in shaping levels of consumer discrimination against businesses. The accessibility of race as a dominant category for in-group and out-group distinction has been shown to influence various outcomes for the minoritized groups, ranging from housing discrimination against Arab Americans[86] to evaluative bias and discrimination against African American job applicants and entrepreneurs[87,88]. Our research establishes the pandemic-driven blaming of Asians as one instantiation of mega-threats, referring to negative, identity-relevant societal events that receive significant media attention[89] in the context of entrepreneurship and consumers. Entrepreneurship has historically served as a viable exit strategy for populations facing labour discrimination. However, for businesses serving customers outside their ethnic community of origin, consumer discrimination can hamper the economic viability businesses. If levels of consumer discrimination fluctuate based on current events, otherwise-profitable businesses may quickly become unviable during periods of high discrimination and violence. Furthermore, unpredictability of demand for the businesses' products may also serve as a barrier to entry for potential entrepreneurs.

https://doi.org/10.1038/s41562-022-01493-6

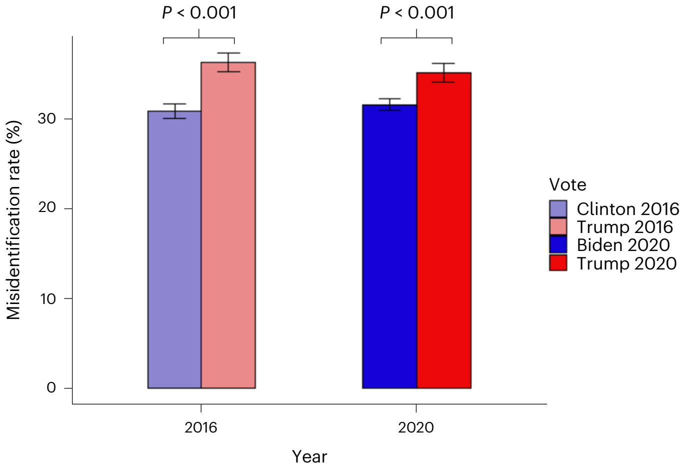

Fig. 6 | Asian restaurant misidentification rate by voting preferences. The misidentification rate of Asian restaurants split on the basis of voting preferences. An MTurk survey was conducted with 2,345 participants (51.3% female; mean age, 39.4 years; age s.d., 12.6 years), who were asked to label a randomly selected sample of real, mono-ethnic restaurants from the SafeGraph dataset by ethnic group. Trump voters in 2016 and 2020 exhibited 36.4% (95% CI = 35.3% to 37.4%) and 35.2% (95% CI = 34.1% to 36.3%) misidentification, respectively. Clinton 2016 and Biden 2020 voters exhibited 30.9% (95% CI = 30.1% to 31.7%) and 31.6% (95% CI = 31.0% to 32.3%), respectively. *P* values were calculated using two-sided *Z*-tests for difference in proportions.

Although our results focus on consumer discrimination against Asian restaurants in the wake of the pandemic, these findings have relevance in a much broader context. Restaurants are a bellwether for broader anti-minority-group sentiment and its impact on small businesses owing to their ubiquity and easy association with an ethnic group. Other small businesses, such as dental offices, lawyers, doctors and accountants, are also easily affiliated with an ethnic group due to typical naming conventions, and our conclusions on how restaurant avoidance is not explained by consumer health safety concerns have substantial implications for consumer discrimination against these businesses as well. There are numerous historical examples of anti-ethnic sentiment due to major geopolitical events, including anti-Arab/Islam and anti-French (Freedom Fries) sentiment in the aftermath of the 9/11 attacks and anti-Japanese sentiment amidst rising American–Japanese competition in the 1980s. However, despite numerous reports of attacks on minorities and anecdotal reports of consumer discrimination, there are considerable difficulties with quantifying the impacts that these crises had on minority-group-owned businesses. The recent pandemic has coincided with major technological advances in location data availability, enabling a granular, quantitative analysis of the impacts on small businesses and misidentification-related spillovers, which were not possible during previous crises.

Second, our research uncovers consequences that may have gone unnoticed. Recent research has documented the rise of racial discrimination and prejudice against Asians and Asian Americans, which resulted in poorer mental and physical health[90] and marginalization[91] in these groups. Other studies on anti-Asian discrimination during the pandemic have relied heavily on data from self-reported incidents of hate against Asian Americans[35] and police statistics[92] on violent attacks; by contrast, our study examines more subtle social and economic impacts of discrimination that are highly relevant to the lives of Asian Americans yet might not rise directly to the level of hate or violence. This study avoids the selection biases of self-reporting or police reporting, whereby immigrant groups may be hesitant to contact authorities[93], and it uses a big-data approach to the question of discrimination covering hundreds of billions of trips to six million locations throughout the United States in comparison to the approximately 9,000 self-reported hate incidents and only 279 hate crimes identified by the FBI against Asian Americans in 2020.

Finally, our study contributes to the psychological theories of collective blame by highlighting the role of ethnic misclassification in consumer discrimination. By examining the costs incurred by both Chinese and non-Chinese Asian restaurants, we capture the process of blame spillover from businesses associated with one ethnic group to the larger tangentially related populations. This spillover effect, at least partly fuelled by the 'yellow peril' stereotype for Asians in general[34] lends support to the theory of collective blame[94–96] that arises from out-group homogeneity bias and cross-race effects. Our study of consumer discrimination demonstrates these spillover effects through ethnic misclassification in an ecologically valid setting. For example, cross-race effects have been found in people's perception of out-group members' faces. Our research extends this line of work by showing that a similar pattern occurs for consumer perception of out-group-owned businesses as well. Studying consumer discrimination based in ethnic and racial misclassification also advances our understanding of the experiences of individuals and entities that are regularly misclassified. For example, research on racial misclassification[97] identified the negative psychological consequences for American Indians who were often misclassified as a different racial group. Our research stresses the prominence of a similar mechanism for Asians who are not ethnically Chinese, and broadens it to encompass social and economic costs.

Limitations

A number of limitations of this research derive from the fact that the onset of COVID-19 was a single, unprecedented shock to public health and the global economy. As previously highlighted, we were unable in the present data to directly quantify the relative roles of supply versus demand side explanations for the observed drops in traffic, although we offer evidence that a purely supply-driven mechanism is unlikely. Moreover, we cannot entirely disentangle the relative role of political leaders' anti-Asian rhetoric from endogenous anti-Asian sentiment arising from the public health threat itself. History has repeatedly shown that blaming marginalized groups for public health crises is sadly quite common[31,32]. For example, Irish immigrants were blamed as the bearers of cholera, and Jewish immigrants were blamed for tuberculosis[98]. More recently, African and Chinese cultural habits were also blamed for the outbreaks of Ebola and SARS[99], and Latino individuals were blamed for the spread of H1N1[14]. It is possible that anti-Asian sentiment would have arisen even in the absence of statements by public officials targeting Asians. Alternatively, politicians' statements stigmatizing the pandemic could be a reflection of constituents' pre-existing beliefs rather than formative of those beliefs. Although we cannot reliably create a counterfactual world in which COVID-19 was not followed by anti-China rhetoric by the US political leaders, this is a ripe area for future research to further examine the relative importance of different triggers for anti-Asian sentiment, discrimination and behaviour.

Conclusion

Here we examined the effects of anti-Asian sentiment on consumer discrimination against restaurants associated with Asian Americans. Leveraging and documenting the COVID-19 pandemic as an exogenous shock to anti-Asian sentiment, we found a marked and substantial decrease in visits to both Chinese and non-Chinese Asian restaurants. Consistent with partisan-cuing theories, we found that this effect is most prominent in areas with more Trump voters. Although Trump voters were not more likely to express safety concerns with consumption of Chinese food, they were significantly more likely to attribute blame for pandemic spread to Asian or Chinese people. This suggests that anti-Asian sentiment drove restaurant avoidance beyond perceived risk of contracting COVID-19. Finally, we examined a potential driver of spillovers to non-Chinese Asian restaurants in ethnic misidentification. Consistent with our hypotheses, survey responses showed that individuals who incorrectly believed that the majority of Asian Americans were Chinese also expressed greater fear of Chinese food, and Trump support was a strong and significant positive predictor of avoidance of non-Chinese Asian restaurants and ethnic misidentification of Asian restaurants. Taken together, these findings indicate that anti-China sentiment—regardless of whether it was driven by fear or anger—triggered by COVID-19 and reinforced by US political rhetoric had a substantial role in consumer discrimination against Asian-owned restaurants.

Concerns about rising anti-Asian discrimination extend far beyond the consequences of the COVID-19 pandemic. Asian Americans have made up the plurality of immigrants to the United States since 2008 (ref. 100). Historically, the large increases in California's Chinese immigrant population during the nineteenth century were swiftly followed by a sharp increase in anti-Asian sentiment and discrimination, which persisted even after legislation stopped the flow of new immigrants from Asia[12,101]. In addition to this historical example, recent research[102] has found that, as minority groups increase in rank in terms of their relative size (for example, to the largest minority group within a community), negative attitudes and violence towards these minority groups increase as well. Together with our own findings, these examples suggest that the United States may be entering a longer period of increased anti-Asian sentiment, which makes understanding the effects of discrimination against this group even more important.

Finally, although this research focuses on stigmatization and discrimination against Asian Americans, the findings have broader implications for public policy and communications strategy. Given the long history of stigmatization, discrimination and violence after major world events, this research underlines the responsibility of policymakers and officials to carefully consider the risks to minority and marginalized communities before responding.

Methods

Our research complies with all relevant ethical regulations. The Institutional Review Board for Health Sciences and Behavioral Sciences at the University of Michigan reviewed the survey studies and determined that they were exempt from further review. The anonymized and aggregated data do not involve 'human subjects' as defined. The participants were compensated for their time, and informed consent was obtained from all of the human participants in our surveys.

Data overview

We used four main data sources to determine the relationship between COVID-related anti-Asian sentiment and consumer discrimination against restaurants, including Google Trends, SafeGraph aggregate mobility data, surveys on anti-Asian attitudes and a survey on restaurant ethnic misidentification.

To broadly summarize, we used the web search data from Google Trends covering January 2016 to August 2020 to highlight the nature of the exogenous shock to American conceptions of China and Chinese food during COVID-19. We analysed movement data provided by SafeGraph over the period 4 November 2019 to 7 June 2020 to directly measure consumer discrimination in the form of visits to Asian (including both Chinese and non-Chinese) and non-Asian restaurants, supplementing our analysis with US elections and census data to examine heterogeneity in measured effects. We then turned to understanding the underlying psychological mechanisms behind these forms of discrimination. We gathered survey data from 4,000 Americans (in four waves fielded 5 May 2020, 27 August 2020, 29 October 2020 and 15 April 2021) to determine whether they blamed Chinese and other Asian American populations for COVID-19, and how this blame related to their beliefs about Chinese food safety. Finally, we used a survey of 2,345 Americans collected from 27 March 2021 to 8 May 2021 to understand whether the spillover effects were driven by ethnic misidentification of other Asian restaurants as Chinese restaurants. The full list of survey questions are provided in the Supplementary Information.

Search data

Weekly search data on US searchers from Google Trends enabled us to examine the role of the COVID-19 pandemic as an exogenous shock to anti-Asian sentiment during 2020. Google Trends data have been shown to be a powerful measure of racial animus[103] that correlates strongly with a wide variety of outcomes, including electoral[103] and health outcomes[104]. Supplementary Table 3 provides the full information on the search queries that we examined, which can be broadly classified into anti-China and food-safety related. We examined these queries at the weekly level from January 2016 to August 2020. Although there is occasional seasonality within search data (for example, people showing a special interest in Chinese food on Christmas Day), comparing searches over the course of five years eliminates the possibility that any patterns that we see in 2020 are the result of seasonal fluctuations.

Aggregate consumer mobility data

We analysed aggregate consumer mobility data provided by the firm SafeGraph using an observation period from 4 November 2019 to 7 June 2020. SafeGraph captures mobile device location data combined with labels defining the perimeters of approximately 5 million points of interest (POI) across the United States to generate weekly aggregated counts of visitors to each POI. We filter the week–POI aggregated visit counts to isolate data from 381,692 unique restaurant locations. We focused on restaurants specifically owing to their ubiquity, ease of affiliation between the business and a particular ethnic group, the increase in food-safety-related searches following COVID-19, and historical and contemporary use of food stereotypes as an outlet for xenophobic sentiment.

Attitudinal survey data

We ran two samples of 1,000 respondents for the same set of questions (noted as survey 1) conducted on 5 May 2020 (57% female; mean age, 43 years; age s.d., 16 years) and 27 August 2020 (55% female; mean age, 42 years; age s.d., 15 years) and a slightly updated version (survey 2) on 19 October 2020 (57% female; mean age, 38 years; age s.d., 13 years). We ran a final survey, also 1,000 respondents (49% female; mean age, 39 years; age s.d., 11 years), on 15 April 2021 (survey 3). The multi-waves were designed to capture the trends in our core questions of sentiment and behaviour as the pandemic progressed. Surveys were conducted within native advertising units in a mix of mobile applications on both iOS and Android, and in both mobile and desktop web experiences, using the Pollfish interface and delivery mechanism. The participants were at least 18 years old, and were randomly selected from the pool of eligible respondents. We asked a total of 25 questions in survey 1 and 18 questions in surveys 2 and 3 (see the Supplementary Information for a full list of questions, including both exploratory questions as well as specific questions to be used in this paper). These survey results were raked to reflect national Census estimates of key demographics.

Restaurant confusion survey data

We ran a separate survey study from 26 March 2021 to 8 May 2021 to examine the degree to which individuals distinguish between various Asian restaurants. A total of 2,345 American participants (51.3% female; mean age, 39.4 years; age s.d., 12.6 years) who were eligible to vote in 2016 and 2020 were recruited through Amazon Mechanical Turk (MTurk). The 2,000 restaurants in the pool were chosen in a stratified random sampling from among mono-ethnic restaurants in the SafeGraph dataset. Each participant was asked to classify a randomly selected set of 20 restaurants based on name alone from the pool of 2,000 real restaurants. Our stratification was chosen to balance between the most common ethnic restaurant cuisines while oversampling Chinese restaurants, as they were the focus of messaging and food safety concerns. The sample included 400 Chinese restaurants and 200 each of French, Indian, Italian, Japanese, Korean, Mexican, Thai and Vietnamese restaurants. The participants were also asked to self-report their gender, age, ethnicity and voting preferences in both the 2016 and 2020 American presidential election.

Panel regression model for measurement of pandemic traffic impacts

Our analysis of the consumer mobility data follows a difference-in-difference framework, measuring the differential impact of the onset of COVID-19 on visits to Asian versus non-Asian restaurants. This analysis controls for persistent differences in traffic for each restaurant and common temporal shocks. Specifically, we estimate the following equation:

$$\text{logVisits}_{it} = \beta_1 \times I(\text{Asian}_i \times \text{postCOVID}_t) + \beta_2 \times \text{CaseRate}_{jt} + \eta_i + \delta_t + \epsilon_{it} \quad (1)$$

In this model, i indexes restaurant locations and t indexes the weeks from 4 November 2019 to 7 June 2020. logVisits_{it} is the natural log of the visit count to restaurant i in week t, and CaseRate_{jt} is the number of per capita reported cases of COVID-19 in week t for the ZIP code j containing the restaurant i. Our difference-in-difference measure of interest is β_1, which captures the interaction between whether the restaurant i is classified as an Asian restaurant and whether the time t is after 13 March 2020—the major onset of COVID-19 in the United States and declaration of National Emergency. η_i denotes restaurant-level fixed effects capturing persistent differences in traffic for each restaurant location. These η_i values collectively capture differences between Asian and non-Asian restaurants, and therefore replace the need for an indicator on Asian restaurants in the typical difference-in-difference specification. δ_t captures common temporal shocks to traffic, such as if outdoor dining restrictions impacted all restaurants post-COVID or if there was a reduction in traffic due to national holiday.

This regression framework enables us to estimate the average traffic impact of the pandemic to Asian restaurants relative to non-Asian restaurants. Our specification is log-linear and, therefore, the estimated impact coefficient of −0.2013 can be interpreted as us observing an average decline in traffic of 18.4% ($e^{-0.2013} = 1 - 0.184$) for Asian restaurants in the post-COVID period when holding all other variables equal. This procedure is replicated to focus on the subsets of Chinese and non-Chinese Asian restaurants, holding the comparison group of non-Asian restaurants each time. Finally, the heterogeneity analysis calculates the impact coefficients separately for each ZIP code. These coefficients are visualized in Fig. 2 and regressed on the Trump 2016 vote share within the ZIP code while controlling for ZIP code median household income, college education and racial demographics to generate the results observed in Table 2.

We used a counterfactual simulation and back-of-envelope calculations to extrapolate the measured drop in Asian restaurant traffic into dollar terms. We simulated a counterfactual in which Asian restaurants suffered no relative traffic penalty versus non-Asian restaurants after the onset of COVID-19 by setting the interaction term in our regression model to zero. The model predicts that an additional 4.01 million SafeGraph-recorded visits to Asian restaurants would have occurred during our post-pandemic onset observation period, or an additional 13.2 million SafeGraph visits when prorated through the end of 2020. To perform the back-of-envelope calculation, we make the necessary and simplifying assumption that each restaurant's revenue is directly proportional to its SafeGraph traffic. The US Census Bureau estimates that total US restaurant revenue was US$584 billion in 2020 (ref. 105), which is allocated evenly across the estimated 1.04 billion SafeGraph restaurant visits in 2020. We therefore arrive at our estimate that American consumer avoidance of Asian restaurants led to $7.42 billion in lost revenue for those businesses in 2020.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

The aggregated consumer mobility data used in this study are derived from the Weekly Patterns and Core Places datasets provided under a free academic license from SafeGraph; however, license restrictions do not allow for the datasets to be made publicly available. Academic researchers can request free access to SafeGraph data through their Dewey partnership program (https://www.safegraph.com/blog/safegraph-partners-with-dewey). The survey data were collected for this study through Pollfish and Amazon Mechanical Turk and are available online (https://osf.io/gazwb/?view_only=cafc11d21236433caa3781748416fa9d). Finally, this study uses publicly available datasets on Google search (https://trends.google.com/trends/) COVID-19 cases (https://www.nytimes.com/article/coronavirus-county-data-us.html), US Census information (https://www.census.gov/data.html), and 2016, 2018 and 2020 US election results (https://electionlab.mit.edu/data). Source data are provided with this paper.

Code availability

Analysis of the consumer mobility data was performed using R v.4.0.3 and Python v.3.8.3. Analysis of survey data was performed using R v.4.0.3. Analysis of online search data was performed using R v.4.0.2 and Python v.3.5.2. All analysis code used in this study has been deposited at the Open Science Framework repository (https://osf.io/gazwb/?view_only=cafc11d21236433caa3781748416fa9d).

References

1. Bertrand, M. & Mullainathan, S. Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination. *Am. Econ. Rev.* **94**, 991–1013 (2004).
2. Pager, D. The mark of a criminal record. *Am. J. Sociol.* **108**, 937–975 (2003).
3. Kuppuswamy, V. & Younkin, P. Testing the theory of consumer discrimination as an explanation for the lack of minority hiring in Hollywood films. *Manage. Sci.* **66**, 1227–1247 (2020).
4. Acquisti, A. & Fong, C. An experiment in hiring discrimination via online social networks. *Management Science* **66**, 1005–1024 (2020).
5. Chavez, K. Penalized for personality: a case study of Asian-origin disadvantage at the point of hire. *Sociol. Race Ethnicity* **7**, 226–246 (2021).
6. Broyles, P. & Fenner, W. Race, human capital, and wage discrimination in stem professions in the United States. *Int. J. Sociol. Social Pol.* **30**, 251–266 (2010).
7. Dustmann, C. & Theodoropoulos, N. Ethnic minority immigrants and their children in britain. *Oxford Econ. Pap.* **62**, 209–233 (2010).
8. Ghazaryan, A. *The Impact of Labour Market Discrimination on Welfare Dependency of Second Generation Immigrants in the UK*. University of Southampton Discussion Papers in Economics and Econometrics No. 1901 https://www.southampton.ac.uk/economics/research/discussion_papers.page (2019).
9. Quillian, L., Lee, J. J. & Honoré, B. Racial discrimination in the US housing and mortgage lending markets: a quantitative review of trends, 1976–2016. *Race Soc. Probl.* **12**, 13–28 (2020).
10. Mason, P. L., Conrad, C., Whitehead, J., Mason, P. & Stewart, J. (eds) *African Americans in the US Economy* 141–150 (Rowman & Littlefield Publishers, 2005).
11. Quillian, L., Pager, D., Hexel, O. & Midtbøen, A. H. Meta-analysis of field experiments shows no change in racial discrimination in hiring over time. *Proc. Natl Acad. Sci. USA* **114**, 10870–10875 (2017).
12. Liu, H. *From Canton Restaurant to Panda Express* (Rutgers University Press, 2015).
13. White, R. *Railroaded: The Transcontinentals and the Making of Modern America* (WW Norton & Company, 2011).

14. McCauley, M., Minsky, S. & Viswanath, K. The H1N1 pandemic: media frames, stigmatization and coping. *BMC Publ. Health* **13.1**, 1116 (2013).
15. Chandrasekhar, C. A. Flying while brown: federal civil rights remedies to post-9/11 airline racial profiling of South Asians. *Asian Law J.* **10**, 215–251 (2003).
16. Johnson, P. The social construction of identity in criminal cases: cinema verite and the pedagogy of Vincent Chin. *Mich. J. Race Law* **1**, 347 (1996).
17. Quattrone, G. A. & Jones, E. E. The perception of variability within in-groups and out-groups: implications for the law of small numbers. *J. Pers. Soc. Psychol.* **38**, 141–152 (1980).
18. Chance, J. & Goldstein, A. Depth of processing in response to own- and other-race faces. *Pers. Soc. Psychol. Bull.* **7.3**, 475–480 (1981).
19. Lebrecht, S., Pierce, L., Tarr, M. & Tanaka, J. Perceptual other-race training reduces implicit racial bias. *PLoS ONE* **4.1**, e4215 (2009).
20. Bursztyn, L., Chaney, T., Hassan, T. A. & Rao, A. *The Immigrant Next Door: Exposure, Prejudice, and Altruism* w28448 (National Bureau of Economic Research, 2021).
21. Zebrowitz, L., White, B. & Wieneke, K. Mere exposure and racial prejudice: exposure to other-race faces increases liking for strangers of that race. *Soc. Cogn.* **26.3**, 259–275 (2008).
22. Wu, F. H. Where are you really from? Asian Americans and the perpetual foreigner syndrome. *Civil Rights J.* **6**, 14 (2002).
23. Lee, S. J. et al. in *Asian American Psychology* (eds Tewari, N. & Alvarez, A.) 119–134 (Psychology Press, 2008).
24. Handron, C., Kirby, T. A., Wang, J., Matskewich, H. E. & Cheryan, S. Unexpected gains: being overweight buffers Asian Americans from prejudice against foreigners. *Psychol. Sci.* **28**, 1214–1227 (2017).
25. Borjas, G. J. & Bronars, S. G. Consumer discrimination and self-employment. *J. Polit. Econ.* **97**, 581–605 (1989).
26. Fairlie, R. W. The absence of the African-American owned business: an analysis of the dynamics of self-employment. *J. Labor Econ.* **17**, 80–108 (1999).
27. Holzer, H. J. & Ihlanfeldt, K. R. Customer discrimination and employment outcomes for minority workers. *Q. J. Econ.* **113**, 835–867 (1998).
28. Liu, F., Liao, X. & Ming, C. Prejudice, does it exist or not? Consumer price discrimination in minority entrepreneurship. *Front. Psychol.* **11**, 2180 (2020).
29. Younkin, P. & Kuppuswamy, V. The colorblind crowd? founder race and performance in crowdfunding. *Manage. Sci.* **64**, 3269–3287 (2018).
30. *WHO Issues Best Practices for Naming New Human Infectious Diseases* (WHO, 2015); https://www.who.int/news/item/08-05-2015-who-issues-best-practices-for-naming-new-human-infectious-diseases
31. Perry, P. & Donini-Lenhoff, F. Stigmatization complicates infectious disease management. *AMA J. Ethics* **12.3**, 225–230 (2010).
32. Keusch, G., Wilentz, J. & Kleinman, A. Stigma and global health: developing a research agenda. *Lancet* **367**, 525–527 (2006).
33. Gover, A. R., Harper, S. B. & Langton, L. Anti-Asian hate crime during the COVID-19 pandemic: exploring the reproduction of inequality. *Am. J. Crim. Justice* **45**, 647–667 (2020).
34. Tessler, H., Choi, M. & Kao, G. The anxiety of being Asian American: hate crimes and negative biases during the COVID-19 pandemic. *Am. J. Crim. Justice* **45**, 636–646 (2020).
35. *Stop AAPI Hate National Report* (Stop AAPI Hate, 2021); https://stopaapihate.org/national-report-through-september-2021/
36. Ramachandran, V. Asian-owned businesses say they're reeling from hate and violence, operating in fear. *PBS News Hour* (19 April 2021); https://www.pbs.org/newshour/economy/asian-owned-businesses-say-theyre-reeling-from-hate-and-violence-operating-in-fear
37. Cheng, A., Ong, J. & Ong, P. *Asian American Businesses: Identifying Gaps and Supporting Recovery* (Asian Business Association, 2021); https://www.aasc.ucla.edu/resources/policyreports/ABA_Survey_Brief_Recovery21.pdf
38. Jedwab, R., Johnson, N. D. & Koyama, M. Negative shocks and mass persecutions: evidence from the Black Death. *J. Econ. Growth* **24**, 345–395 (2019).
39. Bejarano, E. *Anti-Immigrant Movement Has History of Politicizing Disease* (Southern Poverty Law Center, 2020); https://www.splcenter.org/hatewatch/2020/04/21/anti-immigrant-movement-has-history-politicizing-disease
40. Kraut, A. M. *Silent Travelers: Germs, Genes, and the Immigrant Menace* (JHU Press, 1995).
41. Markel, H. & Stern, A. M. Which face? Whose nation? Immigration, public health, and the construction of disease at America's ports and borders, 1891-1928. *Am. Behav. Sci.* **42**, 1314–1331 (1999).
42. Green, E. G. et al. Keeping the vermin out: perceived disease threat and ideological orientations as predictors of exclusionary immigration attitudes. *J. Community Appl. Soc. Psychol.* **20**, 299–316 (2010).
43. Krings, F. et al. Preventing contagion with avian influenza: disease salience, attitudes toward foreigners, and avoidance beliefs 1. *J. Appl. Soc. Psychol.* **42**, 1451–1466 (2012).
44. Lemongello, S. Politifact: DeSantis claim that COVID rise is due to illegal border crossings is 'false'. *Orlando Sentinel* (7 August 2021).
45. Wahlstedt, A., Bradley, E., Castillo, J. & Burt, K. G. MSG is A-OK: exploring the xenophobic history of and best practices for consuming monosodium glutamate. *J. Acad. Nutr. Diet.* **122**, 25–29 (2021).
46. Mosby, I. 'That won-ton soup headache': the Chinese restaurant syndrome, MSG and the making of American food, 1968–1980. *Soc. Hist. Med.* **22**, 133–151 (2009).
47. Masters-Waage, T. C., Jha, N. & Reb, J. COVID-19, coronavirus, Wuhan virus, or China virus? Understanding how to 'do no harm' when naming an infectious disease. *Front. Psychol.* **11**, 3369 (2020).
48. Budhwani, H. & Sun, R. Creating COVID-19 stigma by referencing the novel coronavirus as the 'Chinese virus' on Twitter: quantitative analysis of social media data. *J. Med. Internet Res.* **22**, e19301 (2020).
49. He, B. et al. Racism is a virus: anti-Asian hate and counterspeech in social media during the COVID-19 crisis. In *Proc. 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining* 90–94 (2021).
50. Hswen, Y. et al. Association of '#COVID19' versus '#Chinesevirus' with anti-Asian sentiments on Twitter: March 9–23, 2020. *Am. J. Publ. Health* **111**, 956–964 (2021).
51. Miro-Llinares, F. & Rodriguez-Sala, J. Cyber hate speech on twitter: analyzing disruptive events from social media to build a violent communication and hate speech taxonomy. *Int. J. Des. Nat. Ecodyn.* **11**, 406–415 (2016).
52. Müller, K. & Schwarz, C. Fanning the flames of hate: social media and hate crime. *J. Eur. Econ. Assoc.* **19**, 2131–2167 (2021).
53. Pei, X. & Mehta, D. #Coronavirus or #Chinesevirus?!: understanding the negative sentiment reflected in tweets with racist hashtags across the development of COVID-19. Preprint at *arXiv* https://arxiv.org/abs/2005.08224 (2020).
54. Reny, T. T. & Barreto, M. A. Xenophobia in the time of pandemic: othering, anti-Asian attitudes, and COVID-19. *Polit. Groups Ident.* **10**, 209–232 (2022).
55. Dhanani, L. Y. & Franz, B. Why public health framing matters: an experimental study of the effects of COVID-19 framing on prejudice and xenophobia in the United States. *Soc. Sci. Med.* **269**, 113572 (2021).

56. Stephens-Dougan, L. *Race to the Bottom: How Racial Appeals Work in American Politics* (Univ. Chicago Press, 2020).
57. Alicke, M. D. Culpable control and the psychology of blame. *Psychol. Bull.* **126**, 556–574 (2000).
58. Hart, H. L. A. & Honoré, T. *Causation in the Law* (OUP Oxford, 1985).
59. Prosser, W. & Wade, J. *Cases and Materials on the Law of Torts* (Foundation Press, 1971).
60. Borah, A. & Tellis, G. J. Halo (spillover) effects in social media: do product recalls of one brand hurt or help rival brands? *J. Market. Res.* **53**, 143–160 (2016).
61. Paruchuri, S. & Misangyi, V. F. Investor perceptions of financial misconduct: the heterogeneous contamination of bystander firms. *Acad. Manage. J.* **58**, 169–194 (2015).
62. Trump, R. K. & Newman, K. P. When do unethical brand perceptions spill over to competitors? *Market. Lett.* **28**, 219–230 (2017).
63. Krupenkin, M., Zhu, K., Walker, D. & Rothschild, D. M. *If a Tree Falls in the Forest: COVID-19, Media Choices, and Presidential Agenda Setting* https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3697069 (2021).
64. Druckman, J. N. The implications of framing effects for citizen competence. *Polit. Behav.* **23**, 225–256 (2001).
65. Lenz, G. S. *Follow the Leader?: How Voters Respond to Politicians' Policies and Performance* (Univ. Chicago Press, 2013).
66. Bullock, J. G. in *The Oxford Handbook of Electoral Persuasion* (eds Suhay, E., Grofman, B. & Trechsel, A. H.) 129 (Oxford Univ. Press, 2020).
67. Weisel, O. Vaccination as a social contract: the case of COVID-19 and US political partisanship. *Proc. Natl Acad. Sci. USA* **118**, e2026745118 (2021).
68. Milosh, M., Painter, M., Sonin, K., Van Dijcke, D. & Wright, A. L. Unmasking partisanship: polarization undermines public response to collective risk. *J. Publ. Econ.* **204**, 104538 (2021).
69. Graham, M. H. & Singh, S. Partisan selectivity in blame attribution: evidence from the COVID-19 pandemic. Preprint at *SocArXiv* https://doi.org/10.31235/osf.io/t8xar (2021).
70. Shepherd, K. John Cornyn criticized Chinese for eating snakes. He forgot about the rattlesnake roundups back in Texas. *The Washington Post* (19 March 2020); https://www.washingtonpost.com/nation/2020/03/19/coronavirus-china-cornyn-blame/
71. Donald Trump calls COVID-19 'kung flu' at Tulsa rally. *The Guardian* (21 June 2020); https://www.theguardian.com/us-news/2020/jun/20/trump-covid-19-kung-flu-racist-language
72. Ostrom, T. M., Carpenter, S. L., Sedikides, C. & Li, F. Differential processing of in-group and out-group information. *J. Pers. Soc. Psychol.* **64**, 21–34 (1993).
73. Mullen, B. & Hu, L.-T. Perceptions of ingroup and outgroup variability: a meta-analytic integration. *Basic Appl. Soc. Psychol.* **10.3**, 233–252 (1989).
74. Krosch, A. R., Berntsen, L., Amodio, D. M., Jost, J. T. & Van Bavel, J. J. On the ideology of hypodescent: political conservatism predicts categorization of racially ambiguous faces as Black. *J. Exp. Soc. Psychol.* **49**, 1196–1203 (2013).
75. Budiman, A. & Ruiz, N. G. *Key Facts About Asian Americans, a Diverse and Growing Population* (Pew Research Center, 2021); https://www.pewresearch.org/fact-tank/2021/04/29/key-facts-about-asian-americans/
76. Warikoo, N. Vincent Chin murder 35 years later: history repeating itself? *Detroit Free Press* (24 June 2017); https://www.freep.com/story/news/2017/06/24/murder-vincent-chin-35-years-ago-remembered-asian-americans/420354001/
77. Fieldstadt, E. Texas ramen shop still requiring masks hit with anti-Asian graffiti. *NBC News* (15 March 2021); https://www.nbcnews.com/news/asian-america/texas-ramen-shop-still-requiring-masks-hit-anti-asian-graffiti-n1261129
78. Wang, C. A year of loss, heartache, looming eviction—and rescuing itself—for Chinatown. *NBC News* (14 December 2020); https://www.nbcnews.com/news/asian-america/year-loss-heartache-looming-eviction-rescuing-itself-chinatown-n1249556
79. Kessler, G. Trump vs. Pelosi: what happened in Chinatown. *The Washington Post* (23 April 2020); https://www.washingtonpost.com/politics/2020/04/23/trump-versus-pelosi-what-happened-chinatown/
80. Yang, S. New York's Chinatown businesses struggle to survive coronavirus shutdown. *Wall Street Journal* (7 May 2020); https://www.wsj.com/articles/new-yorks-chinatown-businesses-struggle-to-survive-coronavirus-shutdown-11588856400
81. Tomassetti, B. Chinatown's pandemic crisis continues. *Fox 5 New York* (10 November 2020); https://www.fox5ny.com/news/chinatowns-pandemic-crisis-continues
82. Manskar, N. Nom Wah, Chinatown's oldest eatery, used frozen dumplings to offset pandemic struggles. *New York Post* (16 July 2020); https://nypost.com/2020/07/16/nom-wah-used-frozen-dumplings-to-offset-coronavirus-struggles/
83. Humphries, S. When fear goes viral: battling prejudice in Chinatown. *The Christian Science Monitor* (10 March 2020); https://www.csmonitor.com/Business/2020/0310/When-fear-goes-viral-Battling-prejudice-in-Chinatown
84. Ostrom, T. M. & Sedikides, C. Out-group homogeneity effects in natural and minimal groups. *Psychol. Bull.* **112**, 536–552 (1992).
85. Farquhar, J. et al. Bruce Lee vs. Fu Manchu: kung fu films and Asian American stereotypes in America. *Bridge Asian Am. Perspect.* **6**, 13–50 (1978).
86. Gaddis, S. M. & Ghoshal, R. Arab American housing discrimination, ethnic competition, and the contact hypothesis. *Ann. Am. Acad. Polit. Soc. Sci.* **660**, 282–299 (2015).
87. Mobasseri, S. Race, place, and crime: how violent crime events affect employment discrimination. *Am. J. Sociol.* **125**, 63–104 (2019).
88. Gorbatai, A., Younkin, P. & Burtch, G. Collateral damage: the relationship between high-salience events and variation in racial discrimination. *Organ. Sci.* https://doi.org/10.1287/orsc.2021.1527 (2021).
89. Leigh, A. & Melwani, S. #Blackemployeesmatter: mega-threats, identity fusion, and enacting positive deviance in organizations. *Acad. Manage. Rev.* **44**, 564–591 (2019).
90. Lee, S. & Waters, S. F. Asians and Asian Americans' experiences of racial discrimination during the COVID-19 pandemic: impacts on health outcomes and the buffering role of social support. *Stigma Health* **6**, 70–78 (2020).
91. Li, Y. & Nicholson Jr, H. L. When 'model minorities' become 'yellow peril'—othering and the racialization of Asian Americans in the COVID-19 pandemic. *Sociol. Compass* **15**, e12849 (2021).
92. Venkatraman, S. Anti-Asian hate crimes rose 73 percent last year, updated FBI data says. *NBC News* (25 October 2021); https://www.nbcnews.com/news/asian-america/anti-asian-hate-crimes-rose-73-last-year-updated-fbi-data-says-rcna3741
93. Yun, I. & Mueller, D. A study of the determinants of reporting crime to the police among Chinese immigrants. *Int. J. Comp. Appl. Crim. Justice* **35**, 53–71 (2011).
94. Denson, T. F., Lickel, B., Curtis, M., Stenstrom, D. M. & Ames, D. R. The roles of entitativity and essentiality in judgments of collective responsibility. *Group Process. Intergroup Relations* **9**, 43–61 (2006).
95. Lickel, B., Miller, N., Stenstrom, D. M., Denson, T. F. & Schmader, T. Vicarious retribution: the role of collective blame in intergroup aggression. *Person. Soc. Psychol. Rev.* **10**, 372–390 (2006).
96. Stenstrom, D. M., Lickel, B., Denson, T. F. & Miller, N. The roles of ingroup identification and outgroup entitativity in intergroup retribution. *Person. Soc. Psychol. Bull.* **34**, 1570–1582 (2008).

97. Campbell, M. E. & Troyer, L. The implications of racial misclassification by observers. *Am. Sociol. Rev.* **72**, 750–765 (2007).
98. Kraut, A. M. Immigration, ethnicity, and the pandemic. *Publ. Health Rep.* **125**, 123–133 (2010).
99. Kapiriri, L. & Ross, A. The politics of disease epidemics: a comparative analysis of the SARS, Zika, and Ebola outbreaks. *Glob. Soc. Welfare* **7**, 33–45 (2020).
100. Budiman, A. *Key Findings About U.S. Immigrants*. Pew Research Center (20 Aug 2020); https://www.pewresearch.org/fact-tank/2020/08/20/key-findings-about-u-s-immigrants/
101. Chiu, H. B. & Kirk, A. T. 'Unlimited American power': how four California newspapers covered Chinese labor and the building of the transcontinental railroad, 1865–1869. *Am. Journal.* **31**, 507–524 (2014).
102. Cikara, M., Fouka, V. & Tabellini, M. *Hate Crime Increases With Minoritized Group Rank* Working Paper 21-075 (Harvard Business School, 2021).
103. Stephens-Davidowitz, S. The cost of racial animus on a Black candidate: evidence using google search data. *J. Publ. Econ.* **118**, 26–40 (2014).
104. Chae, D. H. et al. Association between an internet-based measure of area racism and Black mortality. *PLoS ONE* **10**, e0122963 (2015).
105. *Monthly Retail Trade* (United States Census Bureau, accessed 10 October 2022); https://www.census.gov/retail/index.html

Acknowledgements
We thank the staff at SafeGraph for their free provision of aggregated consumer traffic data to support academic research and our survey participants for their time and attention; Monica Chan, Judith Han and Jared Katzman for their research assistance on this project; and the members of the Ross Behavioral Lab at the University of Michigan for support. We acknowledge the Stephen M. Ross School of Business, University of Michigan, for making funds available to J.T.H. and J.L.C.; Surveys on Pollfish were funded through a general survey research account at Microsoft Research. The authors received no specific funding for this work. Neither funders nor data providers had any role in study design, data collection and analysis, decision to publish or preparation of the manuscript. The findings and conclusions expressed in this article are those of the authors and do not necessarily reflect the views of their institutions. This paper is dedicated to the memories of two Asian Americans—Vincent Jen Chin and Balbir Singh Sodhi.

Author contributions
All of the authors developed the study concept, designed the study, wrote the paper and approved the final version of the paper for submission.

Competing interests
D.R. is an employee of Microsoft Research, but academic work is neither directed nor reviewed by Microsoft Research. The other authors declare no competing interests.

Additional information
Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41562-022-01493-6.

Correspondence and requests for materials should be addressed to Justin T. Huang, Masha Krupenkin, David Rothschild or Julia Lee Cunningham.

Peer review information *Nature Human Behaviour* thanks Luca Fumarco, Jin Goh and Peter Younkin for their contribution to the peer review of this work. Peer reviewer reports are available.

nature portfolio

Corresponding author(s): Justin T. Huang

Last updated by author(s): Oct 12, 2022

Reporting Summary

Nature Portfolio wishes to improve the reproducibility of the work that we publish. This form provides structure for consistency and transparency in reporting. For further information on Nature Portfolio policies, see our Editorial Policies and the Editorial Policy Checklist.

Statistics

For all statistical analyses, confirm that the following items are present in the figure legend, table legend, main text, or Methods section.

n/a	Confirmed	
☐	☒	The exact sample size (*n*) for each experimental group/condition, given as a discrete number and unit of measurement
☐	☒	A statement on whether measurements were taken from distinct samples or whether the same sample was measured repeatedly
☐	☒	The statistical test(s) used AND whether they are one- or two-sided *Only common tests should be described solely by name; describe more complex techniques in the Methods section.*
☐	☒	A description of all covariates tested
☐	☒	A description of any assumptions or corrections, such as tests of normality and adjustment for multiple comparisons
☐	☒	A full description of the statistical parameters including central tendency (e.g. means) or other basic estimates (e.g. regression coefficient) AND variation (e.g. standard deviation) or associated estimates of uncertainty (e.g. confidence intervals)
☐	☒	For null hypothesis testing, the test statistic (e.g. *F*, *t*, *r*) with confidence intervals, effect sizes, degrees of freedom and *P* value noted *Give P values as exact values whenever suitable.*
☒	☐	For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
☒	☐	For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
☒	☐	Estimates of effect sizes (e.g. Cohen's *d*, Pearson's *r*), indicating how they were calculated

Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	Survey data was collected via respondents recruited through Pollfish and Amazon Mechanical Turk utilizing their standard recruiting tools.
Data analysis	Analysis of the consumer mobility data was performed using R version 4.0.3 and Python version 3.8.3. Analysis of survey data was performed using R version 4.0.3. Analysis of online search data was performed using R version 4.0.2 and Python version 3.5.2. All analysis code utilized in this study has been deposited in the Open Science Framework repository accessible through this link: https://osf.io/gazwb/?view_only=cafc11d21236433caa3781748416fa9d

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors and reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Portfolio guidelines for submitting code & software for further information.

Data

Policy information about availability of data

All manuscripts must include a data availability statement. This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A description of any restrictions on data availability
- For clinical datasets or third party data, please ensure that the statement adheres to our policy

Survey data that support the findings of this study have been deposited in an Open Science Framework repository accessible through this link: https://osf.io/gazwb/?view_only=cafc11d21236433caa3781748416fa9d. Consumer mobility data utilized in this study are derived from the Weekly Patterns and Core Places datasets provided under a free academic license from SafeGraph, however license restrictions do not allow the datasets to be made publicly available. Lastly, this study utilizes publicly available datasets on Google search (https://trends.google.com/trends/) COVID-19 cases (https://www.nytimes.com/article/coronavirus-county-data-us.html), US Census information (https://www.census.gov/data.html), and 2016 and 2020 US presidential election results (https://electionlab.mit.edu/data).

Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

☐ Life sciences ☒ Behavioural & social sciences ☐ Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see nature.com/documents/nr-reporting-summary-flat.pdf

Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	This study combines observational data on consumer traffic and search with survey data regarding attitudes towards ethnic groups and restaurant categorization. All data are quantitative.
Research sample	Our consumer mobility data is derived from the Weekly Visits and Core Places datasets from the firm SafeGraph. Based on the firm's descriptions, this data aims to be representative of mobile device users in the US. Online search data is derived from US Google Search Trends. We believe this data is representative of online search patterns in the US. Lastly, our surveys on attitudes towards ethnic groups and restaurant categorization utilized platform standard recruiting tools to recruit representative samples of respondents on the platform. For these studies, participants were at least 18 years old, and recruited from the pool of eligible Pollfish (Wave 1 5/5/20: 57% female, age mean 43, age s.d. 16, Wave 2 8/27/20: 55% female, age mean 42, age s.d. 15, Wave 3 10/29/20: 57% female, age mean 38, age s.d. 13, Wave 4 4/15/21: 49% female, age mean 39, age s.d. 11) and Amazon Mechanical Turk respondents (51.3% female, age mean 39.4, age s.d. 12.6) in the US.
Sampling strategy	We used the standard recruiting tools (convenience sampling) in recruiting participants for both online surveys (attitudinal survey & restaurant categorization survey data) on the online platforms Pollfish and Amazon Mechanical Turk that match researchers with virtual workers/survey takers. We did not perform any sample size calculation, and instead we erred on the side of caution and collected conservatively large samples of 4,000 and 2,345 respondents for our attitudinal & restaurant confusion surveys, respectively. These figures would allow us to make precise inferences even when examining individual waves (1,000 per wave on attitudinal surveys) per recommendations of Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. Educational and Psychological Measurement, 30, 607-610.
Data collection	All survey data have been collected online using mobile devices or personal computers remotely. Experimenters were not blinded to study hypotheses.
Timing	Pollfish surveys on attitudes towards ethnic groups were taken on 5/5/20, 8/27/20, 10/29/20, and 4/15/21. The Amazon Mechanical Turk survey on restaurant ethnic classification was collected between 3/27/21 and 5/8/21. Google Trends Data was gathered on August 2020, querying data spanning Jan 2016 through August 2020. The SafeGraph aggregated consumer mobility data spans Nov 4, 2019 - June 7, 2020.
Data exclusions	No data were excluded.
Non-participation	No participants dropped out/declined participation.
Randomization	Participants in the restaurant confusion study were randomized to see different sets of restaurant names for labeling. Participants in the consumer blame/food safety attitudes study were randomized to see racial groups (blame question) and cuisine types (food safety question) in a randomized order.

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study
☒	☐ Antibodies
☒	☐ Eukaryotic cell lines
☒	☐ Palaeontology and archaeology
☒	☐ Animals and other organisms
☐	☒ Human research participants
☒	☐ Clinical data
☒	☐ Dual use research of concern

Methods

n/a	Involved in the study
☒	☐ ChIP-seq
☒	☐ Flow cytometry
☒	☐ MRI-based neuroimaging

Human research participants

Policy information about studies involving human research participants

Population characteristics	Average age of survey respondents was 39.4, 51.3% female. See above for additional detail.
Recruitment	Survey participants were recruited from available respondents on Pollfish and Amazon Mechanical Turk utilizing their standard recruiting tools. We do not anticipate significant selection bias in this recruitment process which would have impact our results.
Ethics oversight	The IRB HSBS at the University of Michigan has reviewed the two studies and determined that they were exempt from IRB review (Attitudinal survey data: HUM00180988; Restaurant confusion survey data: HUM00195836).

Note that full information on the approval of the study protocol must also be provided in the manuscript.