**Racial Discrimination and Anti-Discrimination: The Impact of the COVID-19 Pandemic on Chinese Restaurants in North America**


## Abstract

The COVID-19 pandemic has led to an increase in cases of racial discrimination against Asians, especially Chinese people. Despite an emerging stream of studies investigating various aspects of the COVID-19 pandemic, research on the behavioral consequences of racial discrimination during the pandemic remains scarce. In this work, we examined how racial discrimination stemming from the COVID-19 pandemic and subsequent anti-discrimination were manifested on online platforms. By conducting difference-in-differences analyses on two large-scale panel datasets from Yelp.com and SafeGraph, we explored the impact of COVID-19 on Chinese restaurants, relative to non-Chinese restaurants, at different phases of the COVID-19 pandemic. We found that the COVID-19 pandemic led to an immediate increase in racial discrimination, which was reflected in a significant drop in the customer patronage frequency of Chinese restaurants as compared to that of non-Chinese restaurants. Furthermore, analyses using multiple behavioral indicators generated by text mining and machine learning techniques consistently suggested that increased discrimination triggered anti-discrimination actions of customers on online platforms after the COVID-19 outbreak. This study contributes to the literature on racial discrimination by investigating a subtle but more factual form of racial discrimination evidenced by the customer patronage of Chinese restaurants, as well as user-generated content, by demonstrating that consumers can fight discrimination on online platforms.



**Keywords:** COVID-19 pandemic, racial discrimination, anti-discrimination, Chinese restaurants

## 1. Introduction

Racial discrimination against ethnic minorities in the U.S. is a longstanding and controversial topic (Quillian et al. 2017, Younkin and Kuppuswamy 2018). Although some types of discrimination gradually diminish, racial discrimination remains a deep-rooted social problem (Quillian et al. 2017). Realizing the importance and substantial adverse impacts of this issue, scholars have extensively examined different types of racial discrimination in the U.S. labor market and how they affect individuals and society at large (Kuppuswamy and Younkin 2020, Younkin and Kuppuswamy 2018).

This research was theoretically motivated by the debate regarding racial discrimination against ethnic minorities. This stream of research has mostly focused on business-to-consumer (B2C) discrimination and peer-to-peer (P2P) discrimination in the marketplace (e.g., Blair et al. 2013, Ge et al. 2020, Gunarathne et al. 2022, Penner et al. 2010, Younkin and Kuppuswamy 2018). Consumer-to-business (C2B) racial discrimination, which captures consumers' choices of businesses in everyday life, is a more subtle but factual form of discrimination as compared to B2C and P2P discrimination. Therefore, research on C2B discrimination remains scant. We extend this stream of literature by considering a unique economic perspective to systematically examine both C2B discrimination and corresponding anti-discrimination in the context of the COVID-19 pandemic.

This research was also practically motivated by the pandemic-induced change in attitudes toward ethnic minorities, specifically Asians, and primarily Chinese in North America, leading to heightened racial discrimination (Lee and Yadav 2020). Thus, an emerging stream of literature has begun to examine the underlying causes, processes, and psychological consequences of racial discrimination induced by the pandemic (e.g., Croucher et al. 2020, Wang et al. 2021). However, these studies have not addressed the following two important questions regarding businesses and customers: (1) How has racial discrimination resulting from the pandemic influenced the behaviors of customers and business performance? (2) How have customers responded to such racial discrimination? Thus, we explored the far-reaching behavioral consequences of both racial discrimination and anti-discrimination against Chinese people during the pandemic in the context of Chinese restaurants.

Specifically, we examined how racial discrimination during the pandemic and the subsequent anti-discrimination were reflected in online reviews for Chinese restaurants in the U.S. and Canada. Chinese restaurants offer an ideal arena to explore how racial discrimination and anti-discrimination manifest in daily life for two reasons. First, ethnic restaurants in the U.S. and Canadian foodservice markets are agents of different ethnic cultures and reflect the cultural and ethnic diversity of these two countries (Barbas 2003). Ethnic restaurants represent avenues through which different races interact with each other frequently, and the attitudes of individuals toward different ethnicities are reflected in their patronage and feedback of various ethnic restaurants. Second, Chinese restaurants have a strong presence in both the U.S. and Canada, and most of their owners are ethnic Chinese; as such, these venues represent Chinese culture to the local population (Fish and Society 2016).

By examining how the pandemic influenced the performance of Chinese restaurants, we explored whether the potential racial discrimination exacerbated by the pandemic exists in the food service industry and how people react to it. Specifically, by applying integrated threat theory (ITT), we first investigated how racial discrimination during the pandemic changed the patronage frequency of Chinese restaurants by non-Chinese customers in the U.S. and Canada. Second, by utilizing intergroup contact theory (ICT), we studied how racial discrimination triggers the anti-discrimination behaviors of individuals, thus impacting their evaluations of Chinese restaurants on online platforms.

Our empirical analysis exploited a dataset that contained detailed information on more than 30,000 restaurants from the largest online review website in the U.S. and Canada, namely Yelp.com. As an online platform, the accessibility that Yelp.com offers to a broad audience enables the capture of nuanced yet factual shifts in user behavior. And it provides an important venue for users' discrimination and anti-discrimination behavior. To identify the differential effects of the pandemic on Chinese and non-Chinese restaurants, we used the outbreak of the pandemic as a quasi-experimental setting and conducted difference-in-differences (DID) analyses. At the restaurant-week level, we found that, compared to non-Chinese restaurants, there was an immediate reduction in the patronage frequency of Chinese restaurants during the outbreak phase of the pandemic. The restaurant industry began to recover after stay-at-home orders were lifted across states, but the patronage frequency of Chinese restaurants remained lower than that of non-Chinese restaurants. Further analyses revealed that this difference was more significant in cities where the Chinese population was more salient (i.e., a more visible and pronounced threat) and in cities where more anti-Asian racial crimes were perpetrated (i.e., a more deeply ingrained racial bias).

Interestingly, we further found that the growing racial discrimination triggered anti-discrimination actions. Specifically, compared to non-Chinese restaurants, consumers gave Chinese restaurants more favorable evaluations and more supportive expressions in their reviews after the outbreak of the pandemic. This effect was more salient in cities where Chinese people were perceived more as a minority group. Analyses using SafeGraph data, two randomized experiments, a series of robustness checks, and falsification tests all validated our main findings.

## 2. Related Work

### 2.1 Racial Discrimination During Public Crises

Racial discrimination refers to "negative and unfair treatment toward a particular group based on their ethnicity or race" (Fish and Syed 2019). Public crises, such as public health crises (McCauley et al. 2013), terrorism (Chandrasekhar 2003), and economic tumult (Johnson 1998), have been documented to lead to discrimination toward minority groups. For instance, the 9-11 terrorist attack in the U.S. triggered the blame of people of Arab and Middle Eastern origin (Chandrasekhar 2003). We contribute to the relevant literature by extending the research scope to the pandemic context and focusing on consumer discrimination in the marketplace (i.e., how consumers discriminated against businesses associated with minority groups during the COVID-19 pandemic), which has been largely ignored in the extant work.

### 2.2 Racial Discrimination in Consumer Markets

Prior research in multiple offline contexts has documented abundant racial discrimination- also referred to as "racial bias" (i.e., the less desirable treatment of consumers from a racial minority)- against ethnic minorities (e.g., African American consumers). These settings include retail (Schreer et al. 2009), housing (Yinger 1986), car sales (Ayres 1995), and healthcare (Blair et al. 2013, Penner et al. 2010). For instance, Schreer et al. (2009) found that retail salespeople showed higher levels of suspicion toward African American customers when they asked a salesperson to remove the security sensor from a pair of sunglasses prior to trying them on in front of a mirror. The foregoing empirical studies on consumer racial discrimination in offline contexts have focused exclusively on B2C racial discrimination, as the perpetrators were employees of different companies, and the victims were customers. Companies are vicariously liable for negligent acts or omissions by their employees.

With the prevalence of online platforms where routine activities occur, racial discrimination has inevitably appeared online. Scholars are investigating the link between internet accessibility and racial discrimination, with studies such as Chan et al. (2016) showing that broadband access spikes racial hate crimes, especially in racially charged regions. At a more granular level, research has documented racial discrimination in a variety of online platforms. These include lodging (Edelman et al. 2017), classified advertisements (Doleac and Stein 2013, Ghoshal and Gaddis 2015), e-commerce (Ayres et al. 2015), lending and crowdfunding (Pope and Sydnor 2011, Younkin and Kuppuswamy 2018), and mobility services (Ge et al. 2020). Most of the empirical research on racial discrimination in online environments has focused on P2P racial discrimination, as "the perpetrators and the victims are individuals acting independently on their own behalf" (Gunarathne et al. 2022, p. 43). From a regulatory perspective, it is commonly established that platforms bear responsibility for discriminatory actions carried out by individual users. Based on the perpetrator and victim dimensions, the existing literature on racial discrimination is summarized in Table A1.

This research explores the less-studied C2B racial discrimination, reversing the usual roles of perpetrators and victims. In previous studies on B2C racial discrimination, the victims were typically considered to be individual customers; this is due to the unequal distribution of market power, where suppliers (businesses) hold a more advantageous position than demanders (customers) (Perloff et al. 2007). However, in the context of P2P racial discrimination, the primary actors are individual users whose level of market power is unlikely to vary significantly. Thus, on some online platforms, such as Airbnb.com and Craigslist, both sides have been identified as victims (Edelman and Luca 2014, Edelman et al. 2017, Doleac and Stein 2013, Ghoshal and Gaddis 2015). This study deviates from these earlier studies by investigating instances of discrimination in which the usually disadvantaged party (customers) discriminates against a relatively more advantageous party (businesses) in consumer markets. It is among the first to explore C2B racial discrimination where customers are perpetrators and ethnic minority-run businesses are victims.

Additionally, perpetrators of C2B discrimination (i.e., customers of Chinese restaurants in this study) conceivably will be unlikely to be held liable for their discriminatory behavior toward the discriminated business entity. Moreover, C2B discrimination captures consumers' patronage of businesses in daily life; as such, it is seemingly a more subtle but factual form of discrimination as compared to B2C and P2P discrimination. Therefore, discrimination in a C2B context is likely more difficult to detect. Considering the insidious nature of C2B discrimination and its outsized impact on business operations (i.e., the impact of discrimination on Chinese restaurants in this study), the study of C2B racial bias is a worthwhile endeavor. Furthermore, to the best of our knowledge, we are also the first researchers to investigate anti-discrimination behaviors of consumers in the same context.

The existing scholarly work that closely aligns with our study is the research by Huang et al. (2023). However, notable distinctions remain between our research and theirs. Specifically, we distinctly center our examination on the dual facets of racial discrimination and anti-discrimination. In contrast, Huang et al. (2023) predominantly directed their focus on one aspect of racial discrimination. Furthermore, this study offers a robust theoretical basis by using ITT and ICT to explain how the pandemic contributed to discrimination against Chinese communities and the resulting anti-discrimination. We also provide theoretical (and empirical) justification for how discrimination and anti-discrimination can be manifested as patronage and consumer feedback. Compared to the study by Huang et al. (2023), in which a limited theoretical lens was used and the use of measures was not rigorously justified, our study provides more theoretical contributions to the literature on both racial discrimination and anti-discrimination. Finally, in alignment with the objectives of our research, we undertake a more exhaustive and encompassing analysis. This includes an examination of anti-discrimination measures, the segmentation of the pandemic timeline into the outbreak and recovery phases, and the utilization of machine learning and controlled experiments, which are complemented by robustness tests to bolster the rigor of our findings and rule out alternative explanations.

**2.3 Anti-Discrimination**

In contrast to racial discrimination, anti-discrimination is a conscious rejection of personal acts of prejudice and racial discrimination (Bowser and Bowser 1995). Anti-discrimination is usually enabled by one's own observations of minoritized people experiencing racial discrimination, the awareness of the harm caused by discrimination, and the desire to act against the existence of racial oppression (Bowser and Bowser 1995, Bonnett 2005, Nelson and Dunn 2011). As the term suggests, to be "anti"-something indicates a degree of effort (Ali et al. 2021); thus, anti-discrimination requires actions that entail a certain amount of effort (Bonnett 2005, Ali et al. 2021). The action is not restricted to "anti-racist movements" by a small coterie of activists; rather, it includes much broader social participation by millions of individuals, either explicitly or implicitly, in their everyday lives (Bonnett 2005). Therefore, the recognition of racial discrimination typically evokes individuals who have anti-discrimination tendencies to engage in endeavors to support minoritized people who experience racial discrimination (Nelson and Dunn 2011).

While racial discrimination has received much attention, anti-discrimination remains relatively unexplored. The most pertinent studies focus on mitigating racial discrimination, such as Pope et al. (2018), who found that racial bias can be mitigated by raising people's awareness of racial bias in the media. Arguably, these studies have provided valuable insight into reducing racial discrimination, but none have investigated actions taken by individuals to fight against racial discrimination. Hence, in addition to examining racial discrimination, we explored how individuals fight against racial discrimination in an online business context.

### 2.4 Anti-Discrimination on Online Platforms

In online consumer markets, one possible, yet overlooked, source with which to capture the anti-discrimination behaviors of individuals is consumer reviews or user-generated content (UGC). Prior research has documented that UGC is perceived to be more credible than marketer-generated content, as customers usually describe a product from their own perspective; thus, UGC is more customer-oriented than is marketer-generated content (Goh et al. 2013). Because of this characteristic, UGC has become an influential force for consumer decision-making and product sales (Goh et al. 2013, Liu et al. 2017).

However, the potential of UGC has yet to be fully utilized. Despite the rise of racial discrimination in online consumer markets, with few exceptions, minimal work has shed light on the subsequent anti-discrimination behavior that could possibly be reflected in customer-oriented reviews. One exception is Cui et al. (2020), whose investigation found that requests from guests with African-

American-sounding names were less likely to be accepted than those with Caucasian-sounding names on the Airbnb platform. Moreover, a positive review posted on a guest's page was found to decrease discrimination significantly toward guests with African-American-sounding names. Moreover, Kaas and Manger (2012) found that bias against ethnic minorities on an online job application was lowered by adding favorable information about the job candidate's personality. Hurd et al. (2022) ascertained that African American students frequently encountered racial discrimination on social media, but found that this harm was mitigated when racial discrimination was challenged by their white peers.

We contribute to the literature on consumers' online anti-discrimination by focusing on reducing discrimination toward businesses and demonstrating that consumers use online postings as a means of fighting against discrimination toward Chinese restaurants.

## 3. Theoretical Background and Hypothesis Development

In this section, we develop our hypotheses regarding how COVID-19 triggered discrimination and anti-discrimination toward Chinese people, eventually influencing Chinese restaurants. First, based on ITT, we discuss how the pandemic triggered racial discrimination toward Chinese communities. Second, relying on ICT, we describe how increased racial discrimination toward Chinese communities triggered individuals' anti-discrimination behaviors. Finally, we hypothesize the impacts of COVID-19 on the customer patronage and customer feedback of Chinese restaurants while taking into account the net effect of discrimination and anti-discrimination.

### 3.1 Racial Discrimination During the Pandemic

Integrating various theoretical perspectives (Rohmann et al. 2006), ITT provides a comprehensive framework for analyzing intergroup relations and discriminatory attitudes based on out-group threats (Stephan et al. 1998). Specifically, ITT proposes four types of threats that can explain and predict prejudicial attitudes toward out-groups: realistic group threats, symbolic group threats, realistic individual threats, and symbolic individual threats (Stephan et al. 2002). According to ITT, intergroup feelings of fear and threat foster discriminatory attitudes (Stephan and Stephan 2000). Even a perceived threat, not necessarily a real threat, can lead to discrimination and hate toward the out-group (Stephan et al. 1998). Harrison and Peacock (2010) suggest ITT is still developing. While applied in business areas like locals' attitudes towards tourists (Ward and Berno 2011), ITT's value in business-related negativity remains untested. Thus, we expanded this literature, primarily immigrant-focused, to examine local discrimination towards Chinese in the context of Chinese restaurants.

Research on evolutionary psychology suggests that the motivation to avoid infectious diseases triggers people's prejudices against subjective out-groups (Schaller and Neuberg 2012). During the pandemic, there has been a salient connection between the COVID-19 virus and Asians, especially Chinese people, on social media (Binder 2020). Then-U.S.-President Donald Trump repeatedly referred to COVID-19 as "the China virus," which fueled the fire. In social psychology, an out-group is a social group with which an individual does not psychologically identify as being a member and from which s/he tends to disassociate (Tajfel 1970). The pandemic amplified perceptions among some Americans that Chinese individuals, being closely associated with the virus, constituted an especially prominent and aversive out-group. Chinese people were distinctly identified on social media as the main out-group, which was deemed a threat to Americans' health (Binder 2020). Consequently, Chinese communities were regarded as a threat to Americans' physical well-being during COVID-19.

According to ITT, even a subjectively perceived threat (i.e., whether the threat is real or not) is sufficient to result in the public's expression of racial discrimination and prejudice toward out-group members (Croucher et al. 2020). Correspondingly, Chinese restaurants— being reflective of the Chinese culture and people—encountered consequential racial discrimination after the outbreak as compared to non-Chinese restaurants.

### 3.2 Anti-Discrimination During the Pandemic

Scholars have confirmed that groups that feel threatened by out-groups tend to have decreased prejudice after interacting with out-groups (Blair et al. 2003, Stephan et al. 2002). The underlying mechanisms of this phenomenon are empathy with the out-group and a reduction in intergroup threat and anxiety (Kanas et al. 2015). Moreover, theoretically, prior research has shown that increased racial discrimination leads to different types of anti-discrimination practices aimed at tackling the manifold ways in which racial discrimination is embodied (Corneau and Stergiopoulos 2012).

The core argument of ICT posits that in-groups interacting more with an out-group tend to develop positive perceptions and fewer negative views of that group (Pettigrew 1998). Indeed, research has revealed that positive and meaningful contact experiences between different races can reduce discrimination (e.g., Pettigrew and Tropp 2008, Vonofako et al. 2007) and also trigger anti-discrimination behavior (e.g., Bowser and Bowser 1995, Cakal et al. 2011). For instance, MacInnis and Hodson (2018) found that upon reaching a contact threshold whereby out-group members are viewed as potential friends, having cross-group friendships that involve the recognition of group differences promotes favorable intergroup behavior, policy support, and collective action aimed at reducing group inequality. Also, Dixon et al. (2010) found that the frequency and quality of interracial contact predicted Caucasian support for both race-compensatory and race-preferential redress policies.

Both anecdotal evidence and theoretical predictions indicate that increased racial discrimination will likely lead to anti-discrimination behaviors as a counter-measure (Bonnett 2005, Corneau and Stergiopoulos 2012, Shen-Berro 2020). In the context of Chinese restaurants during the pandemic, racial discrimination triggered a grassroots initiative termed “Welcome to Chinatown.” This initiative aimed to help increase sales by Chinese businesses by encouraging people to patronize those businesses (Shen-Berro 2020).

Hence, during the pandemic, in which there was an increase in cases of racial discrimination against Chinese people, Chinese restaurants tended to receive more anti-discrimination support than non-Chinese restaurants. First, racial discrimination was prone to be directed at Chinese restaurants, as they are venues that cluster Chinese people. Thus, non-Chinese customers who patronized Chinese restaurants during this time conceivably became aware that Chinese people experienced racial discrimination. Second, the patronage of Chinese restaurants by non-Chinese individuals may well have led to a reasonably high chance of having meaningful and positive contact with Chinese people. Upon recognizing the discrimination faced by Chinese people, such interactions would probably evoke empathy in individuals and their desire to act against it (Pettigrew and Tropp 2008, Kanas et al. 2015). Therefore, we contend that increased racial discrimination toward Chinese people during COVID-19 triggered customers’ anti-discrimination actions in support of Chinese restaurants.

It is worth noting that the manifestation of anti-discrimination actions may exhibit a time-lag effect following the onset of racially discriminatory behavior. This is because anti-discrimination deportment is usually triggered by racial discrimination and thus occurs after discrimination has been demonstrated (Bowser and Bowser 1995, Bonnett 2005, Nelson and Dunn 2011).

### 3.3 Net Effect of Discrimination and Anti-Discrimination on Chinese Restaurants

As discussed in the preceding sections, the outbreak of the pandemic likely triggered both racial discrimination and anti-discrimination toward the Chinese population, which could have subsequently affected Chinese restaurants. In a business context, widely acknowledged pivotal performance indicators for a restaurant, including customer patronage and customer feedback (e.g., Pamuru et al. 2021), may be subject to influences simultaneously arising from both racial discrimination and anti-discrimination. We therefore focus on the pivotal performance indicators and hypothesize the net effect of racial discrimination and anti-discrimination on these indicators during the pandemic.

The patronage frequency of Chinese restaurants could have been greatly reduced by racial discrimination during the pandemic. For individual customers, those with racial discrimination tendencies would probably have switched their dining choices toward non-Chinese restaurants. Specifically, ITT suggests that the increase in perceived threats raises the desire of in-group members to “distance” themselves from out-group members (Branscombe and Wann 1994). Similarly, prior research has shown that “escape” is the action tendency triggered by feelings of threat (Mackie and Smith 2016, Cottrell and Neuberg 2005). Thus, avoidance actions—such as not patronizing Chinese restaurants to minimize contact with Chinese people—would likely be an especially common manifestation of racial discrimination toward Chinese people during the COVID-19 pandemic.

Furthermore, it is conceivable that customers with anti-discrimination inclinations might have increased their patronage of Chinese restaurants. However, the effect of anti-discrimination on increasing customer patronage might not be substantial, given the significant effort and risk of virus transmission associated with dining out in Chinese restaurants during the pandemic. Moreover, there are practical limits to how frequently an individual will be likely to patronize a particular establishment. Thus, the overall numbers of those engaged in anti-discrimination activities were likely not substantial enough to overcome the loss of patronage.

In summation, the frequency of customer visits to Chinese restaurants would likely have been primarily affected by the prevalence of racial discrimination against the Chinese community. Aggregately, the economic gains resulting from the customer patronage frequency would be unequally distributed between Chinese and non-Chinese restaurants, which is a recognized method to capture insidious racial discrimination (Pager and Shepherd 2008). Hence, the following is hypothesized.

***H1**: Chinese restaurants experienced a greater decline in customer patronage as compared to non-Chinese restaurants after the outbreak of the COVID-19 pandemic.*

Conversely, regarding customer feedback, the predominant influencing factor might be inverted. Customers with prejudiced attitudes toward Chinese individuals would be unlikely to leave feedback. Due to their biased inclinations, the likelihood of these customers patronizing Chinese restaurants and subsequently providing feedback would be minimal, as their intention would be to disassociate themselves from those who are considered out-group members (Branscombe and Wann 1994). Furthermore, if, in fact, they did not patronize Chinese restaurants but chose to write negative and fake feedback, many online platforms' content filters would have identified and removed those suspicious or fake reviews (e.g., Yelp). Even in the few instances where such customers did patronize these establishments, any discriminatory content in their feedback would have likely be filtered out by online platforms (Roberts 2016), thereby limiting the degree of negativity in their comments.

On the other hand, for customers exhibiting anti-discrimination tendencies, expressing positive feedback is the most practical strategy to counter racial discrimination. In the food service industry, those who have gone to restaurants and then gained a sense of the systematic difference in the customer patronage frequency of Chinese restaurants as compared to non-Chinese restaurants would likely be aware of the existence of racial discrimination. For such customers, if they wished to take action to fight against discrimination and support Chinese people, the most direct and economically efficient action would be to offer good feedback to the Chinese restaurants that they have visited (Forman et al. 2008, Mudambi and Schuff 2010).

Taken together, different from customer patronage, customer feedback might primarily be influenced by the emergence of anti-discrimination in favor of the Chinese community. Aligning with the notion that anti-discrimination behaviors might display a delayed effect, i.e., they tend to be materialized after the demonstration and recognition of discriminatory practices, we anticipate the effect of COVID-19 on customer feedback to emerge following its impact on customer patronage. Thus, the following hypothesis is put forward.

***H2**: Chinese restaurants received more positive expressions of customer feedback compared to non-Chinese restaurants after the outbreak of the COVID-19 pandemic.*

In the subsequent discourse, given that our primary focus is on racial discrimination and anti-discrimination, we employ these two mechanisms as designations for corresponding sections when they serve as the predominant mechanism.

## 4. Empirical Context and Data

### 4.1 Reviews on Yelp.com

Yelp.com is the largest crowd-sourced review website in the U.S. and Canada. In 2021, the website had 46 million unique visitors to its desktop webpages and 57 million unique visitors to its mobile site. The site collects online reviews of a broad array of firms, such as restaurants, hair salons, and accountants. We focused solely on restaurant reviews. A Yelp webpage typically presents customer reviews, which is the site's basic service, and includes the main body of a business's page and general information, such as contact, location, and reservation details. As shown in Figure 1, a review consists of the customer's information, review, rating stars (ranging between 1 and 5), and date of the review, as well as photos of the customer and business (if uploaded). Other users can leave feedback on the review by clicking "useful," "funny," or "cool" buttons.

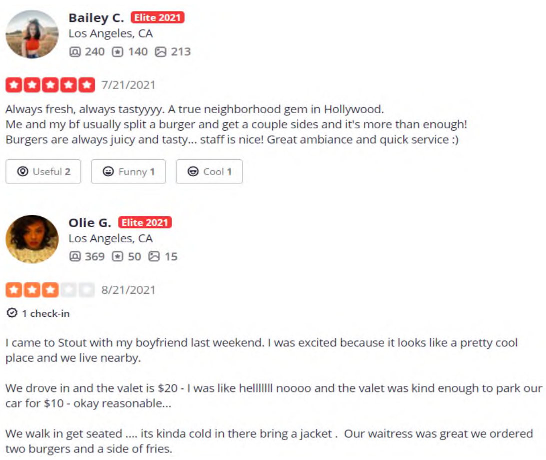


**Figure 1.** An example of a webpage of reviews on Yelp.com.

### 4.2 Data

The data used in this research were sourced from Yelp's annually released academic dataset. We included only restaurants, as per the category list provided by Yelp,[1] and then labeled restaurants serving Chinese food using the same category list. We employed data spanning from the beginning of 2019 to the end of 2020 to investigate the effect of the pandemic. The data included 1,041,586 reviews from 469,614 customers. There were 35,194 restaurants, of which 2,580 (i.e., approximately 7.3%) were Chinese restaurants serving mainly Chinese cuisine, and 32,614 were non-Chinese restaurants. In addition, we extracted features related to services offered by a restaurant from the feature text in the original dataset. The descriptive statistics of the main variables are summarized in Table A2.

Figure 2 depicts the time-series trend of the daily number of reviews in the dataset. There was a sudden fall in early 2020 when COVID-19 first began to spread across the U.S. and Canada. The decline was followed by a slow recovery, but the number of reviews had not yet returned to the 2019 level. This trend indicates that the pandemic had a significant impact on restaurants, as reported by Yelp.com.

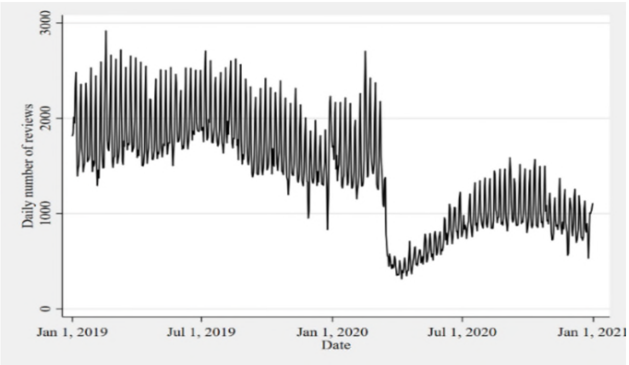


**Figure 2.** The daily number of reviews over time.

The dataset provided a representative sample. The included restaurants were located in nine states and 420 cities in the U.S. and Canada. Geographically, they were located from the west (i.e., Washington, Oregon and Colorado) to the east (i.e., Ohio and Massachusetts), and from the south (i.e., Florida, Texas and Georgia) to the north (i.e., British Columbia). Demographically, the percentage of the Chinese population in each city ranged from 0% (i.e., Davenport, Florida, U.S.) to 53% (i.e., Richmond, British Columbia, Canada). Such significant variation allowed for the examination of the heterogeneity in the effects of the pandemic on racial discrimination and anti-discrimination.

### 4.3 Measures and Validation

[1] https://www.yelp.com/developers/documentation/v3/category_list. Accessed on June 9, 2022.

Theoretically, we have discerned that the pandemic is likely to have had a detrimental effect on the patronage of Chinese restaurants, predominantly via the mechanism of racial discrimination. Conversely, we anticipate a beneficial effect on customer feedback, predominantly via the mechanism of anti-discrimination. In this section, we operationalize customers' patronage and their feedback utilizing data obtained from Yelp. Furthermore, the functional mechanisms driving both outcomes are validated by two online experiments.

**Customer Patronage (Via Racial Discrimination)**. To measure customer patronage, we used the number of customer reviews as a proxy. Previous work has documented the strong relationship between the number of reviews and sales in various industries (Dellarocas et al 2007, Zhang et al. 2013, Zhu and Zhang 2010). Therefore, following Basuroy et al. (2020), Alyakoob and Rahman (2022), and Shen and Wilkoff (2020), we used the number of reviews as a proxy for the patronage frequency of customers. We further statistically validated the correlation between the number of reviews on Yelp.com and restaurant performance (see Section C of the Online Appendix).

A concern that arose was whether fake reviews in our datasets may have biased our analysis and estimations. Fortunately, Yelp employs a robust filter to exclude potentially fake reviews.[2] It is designed to detect solicited reviews and those with conflicts of interest. Luca and Georgios (2016) and Mukherjee et al. (2013) tested the effectiveness of the filter using different approaches, and found that Yelp has efficiently attended to the detection of fake content. This allayed concerns that fake reviews were dominant in the datasets (e.g., review bombing)[3] and thus unlikely to have influenced our findings, which also applies to the analysis of customer feedback.

**Customer Feedback (Via Anti-Discrimination).** Prior to the evaluation of customer-provided feedback, it is imperative to address an associated concern regarding Yelp's claim of filtering discriminatory content.[4] In the absence of effective content moderation, it presents a plausible scenario where the feedback expressed by customers could also be tainted by the mechanism of racial

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[2] https://trust.yelp.com/recommendation-software/. Accessed on June 9, 2022.
[3] See Section K in the Online Appendix, which further reveals the effectiveness of Yelp's fake review filtering mechanism and demonstrates that there was no evidence of review bombing during COVID-19.
[4] https://www.yelp.com/guidelines. Accessed on June 23, 2023

discrimination. We conducted a dictionary-based analysis[5] to look for truly racist reviews, and the results confirmed the effectiveness of Yelp's content moderation.

For a comprehensive evaluation of customer feedback, we incorporated both quantitative ratings and qualitative review content, and constructed the measures *rating* and *premium in rating* to gauge behaviors mainly prompted by anti-discrimination. First, high ratings are a credible customer effort to counter racial discrimination's damaging effects on Chinese restaurants. High ratings on review platforms such as Yelp.com were particularly helpful in increasing sales and surviving during the pandemic. This is because they serve as the most straightforward reference for potential customers (Clemons et al. 2006). Therefore, we compared the rating of Chinese restaurants with that of non-Chinese restaurants to capture the degree to which customers supported Chinese restaurants, which conceivably reflects their anti-discrimination behavior after the emergence of the pandemic.

In addition to the *rating*, we constructed the novel measure of *premium in rating*, which compared the actual rating given by a customer and the sentiment of the review text.[6] This measure emerged from both anecdotal evidence and the concept of price premiums. First, we conducted a comprehensive qualitative assessment of consumer reviews, and found that they mainly evaluated the food, service, and environment of the focal restaurant. However, there was some anecdotal evidence in our data demonstrating possible discrepancies between the rating and sentiment of a review. For example, in one 5-star review, the customer stated, *"…Normally, I would give it a 4-star rating. However, these are difficult times, and this restaurant has stepped up its game…"* This suggests that the customer offered a 1-star premium in the rating because s/he wanted to support the restaurant during COVID-19.

Second, building on anecdotal evidence, we borrowed the idea of the price premium, which refers to the part of the price exceeding (or falling short of) a benchmark price of a product (e.g., Chu et al. 2021). The sentiment of a review can reflect a consumer's fair evaluation of the quality of a product (Luo et al. 2017); in our context, this refers to the food, service, and environment of the restaurant. Theoretically, sentiments should be highly correlated with ratings (Chevalier and Mayzlin 2006), and any difference between the two for a customer should be systematic across restaurants.

[5] The details can be found in Section K of the Online Appendix.
[6] The details of constructing "*premium in rating*" can be found in Section J of the Online Appendix.

However, under some circumstances, such as during the pandemic, the premium in rating likely indicated the extent to which a customer supported certain groups of restaurants. If such support was disproportionally heavily distributed to Chinese restaurants that experienced racial discrimination during COVID-19, it should indicate customers' anti-discrimination in the aggregate.

As described in Section 7.1, we also employed text mining and machine learning techniques to extract other metrics from consumer reviews as alternative measures (i.e., *general support* and *specific support for Chinese*). These efforts helped validate the robustness of our findings.

**Validation of the Predominant Mechanism**. Because racial discrimination is insidious, its detection is challenging (Bonilla-Silva 2012); additionally, the literature on anti-discrimination remains sparse. Thus, the empirical validation of our particular measures was warranted. To achieve this, we ran two controlled experiments, the primary purpose of which was to check the robustness of our results and test the mechanisms (see Section 8.2). Specifically, Experiment 1 sought to examine the impact of COVID-19 on racial discrimination against Chinese people and the subsequent customer patronage and feedback of Chinese restaurants. We found that the threat-triggered discrimination toward Chinese people was manifested as the reduced patronage frequency of Chinese restaurants ($M_{post\text{-}COVID}$ = 3.68 vs. $M_{pre\text{-}COVID}$ = 5.53, $p$ < .001) instead of more negative comments ($M_{post\text{-}COVID}$ = 2.23 vs. $M_{pre\text{-}COVID}$ = 2.32, $p$ = .44). Experiment 2 sought to examine the impact of COVID-19 on anti-discrimination and the subsequent customer patronage and customer feedback. We found that the awareness of discrimination triggered participants' anti-discrimination toward Chinese people, which was manifested as increased positive comments ($M_{post\text{-}COVID}$ = 4.24 vs. $M_{pre\text{-}COVID}$ = 4.05, $p$ = .02) instead of the increased patronage frequency of Chinese restaurants ($M_{post\text{-}COVID}$ = 4.48 vs. $M_{pre\text{-}COVID}$ = 4.36, $p$ = .23). Details of these two experiments are reported in Section A of the Online Appendix.

## 5. Methods

### 5.1 COVID-19 Phases

We first identified time periods when the pandemic exerted differential impacts on the public. On January 30, 2020, the World Health Organization (WHO) declared the novel coronavirus the sixth public health emergency of international concern (PHEIC).[7] Around that date, COVID-19 began to spread quickly throughout the U.S. and Canada. Considering that people would have probably been more sensitive to the local situation than to the global situation, we deemed the date of the first reported COVID-19 case in each state to be the starting point of the pandemic in that state.

To further understand the temporal dynamics of people's racial discrimination and anti-discrimination during the pandemic, we segmented the evolutionary process of COVID-19 dispersion into two phases. The first phase occurred when COVID-19 initially emerged and caused a dramatic decline in customer patronage. Varying across states, this phase spanned from the date of the first reported case in a state to the date when that state issued its stay-at-home order (i.e., the outbreak phase). The second phase occurred when restaurants began recovering from the impact of the pandemic. This phase varied by state and spanned from the date a state lifted its stay-at-home order to the end of 2020 (i.e., the recovery phase). The stay-at-home period was not included in our analysis, as dining at restaurants was prohibited, and not every restaurant provided take-out or delivery service. The customer patronage of most restaurants fell to zero (see the lowest point of Figure 2). Table A3 presents the dates of the first COVID-19 case, stay-at-home order issuance, and reopening in each state.

In nine states, the outbreak phase averaged four weeks in length, and the recovery phase averaged seven months in duration until the end of 2020. We used four months before the emergence of the pandemic as the pre-outbreak phase to compare the changes between Chinese and non-Chinese restaurants before and after the COVID-19 outbreak. Sensitivity analyses with different definitions of the outbreak and recovery phases were also conducted (see Section H of the Online Appendix).

### 5.2 Sample and Model Specifications

**Sample.** ITT suggests that the discriminatory attitudes of in-groups are fostered by their perceived threat from out-groups (Stephan et al. 2002). Moreover, as noted previously, intergroup contact helps facilitate anti-discrimination acts (Pettigrew 1998). Based on the theoretical evidence, we focused on the discrimination and anti-discrimination behaviors of non-Chinese customers during

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[7] On January 30, 2020, the WHO's announcement came as more than 9,800 cases of the virus and over 200 deaths had been confirmed around the globe. This was the sixth time the WHO had issued the PHEIC declaration, as the organization reserves the designation for "extraordinary events" that pose an international threat. Previous announcements included the Ebola and Zika outbreaks.

the pandemic. Specifically, we employed the most accurate, fine-grained race classifier, namely *NamePrism* (Ye et al. 2017), to identify the race of each customer based on his/her name (see Section B of the Online Appendix).

**Racial Discrimination**. Based on the time periods identified, we first investigated how COVID-19 impacted the patronage frequency of customers in restaurants. Specifically, we employed a DID estimator to quantify the differential impact of COVID-19 on customers' patronage frequency of Chinese and non-Chinese restaurants. To gain a granular understanding of the impact of COVID-19, we conducted the analysis at the restaurant-week level. The DID model is as follows:

$$\begin{aligned} Y_{it} = \alpha_i + \delta_t + \beta_1 \cdot Outbreak_{it} + \beta_2 \cdot Chinese_i \times Outbreak_{it} \\ + \beta_3 \cdot Recovery_{it} + \beta_4 \cdot Chinese_i \times Recovery_{it} + \varepsilon_{it} \end{aligned}, \quad (1)$$

where $i$ and $t$ respectively represent the restaurant and week, $Y_{it}$ is the number of reviews from non-Chinese customers of restaurant $i$ in week $t$, $\alpha_i$ is the restaurant fixed effects controlling for time-invariant factors that characterize a restaurant, and $\delta_t$ reflects the monthly fixed effects controlling for the seasonal variation in customer patronage. Moreover, $Chinese_i$ was equal to one if restaurant $i$ was a Chinese restaurant, and zero otherwise. $Outbreak_{it}$ was equal to one if week $t$ was within the outbreak phase of the state where restaurant $i$ was located, and $Recovery_{it}$ was equal to one if week $t$ was within the recovery phase of the state where restaurant $i$ was located. Data during the stay-at-home period were excluded. Of primary interest were $\beta_2$ and $\beta_4$, which capture the estimated effects of COVID-19 on the patronage frequency of non-Chinese customers during the outbreak and recovery phases, respectively.

Because our dependent variable was in the form of counts, we employed a fixed-effects Poisson pseudo-maximum likelihood (PPML) estimator for model estimation (Azoulay et al. 2010, Burtch et al. 2018, Greenwood and Gopal 2015). Standard errors were clustered at the restaurant level to account for potential serial autocorrelation. The PPML estimator provides consistent and robust standard errors even under the condition of overdispersion (Wooldridge 1997). Moreover, simulation evidence has demonstrated the excellent performance of the PPML estimator when there are many zeros in the data (Silva and Tenreyro 2011). This feature is especially important because our analysis was at the granular restaurant-week level (we also used a zero-inflated estimator as a robustness check).

**Anti-Discrimination**. We further performed an analysis of the review rating and premium in rating to assess the anti-discrimination tendencies of non-Chinese customers. This analysis was carried out at the individual review level. The DID model setup is as follows:

$$\begin{aligned} Y_{ijt} = \alpha_i + \theta_j + \delta_t + \beta_1 \cdot Outbreak_{it} + \beta_2 \cdot Chinese_i \times Outbreak_{it} \\ + \beta_3 \cdot Recovery_{it} + \beta_4 \cdot Chinese_i \times Recovery_{it} + \varepsilon_{ijt} \end{aligned}, \quad (2)$$

where *i* represents a restaurant, *j* represents a customer, *t* reflects the posting time, and $Y_{ijt}$ is the rating score/premium in rating of restaurant *i* at time *t* given by customer *j*. Additionally, $\theta_j$ represents the customer fixed effects capturing the time-invariant characteristics of a customer. The remaining variables retain their definitions as per Model Specification (1). Of primary interest were $\beta_2$ and $\beta_4$, which respectively captured the estimated effects of COVID-19 on customers' evaluations of restaurants during the outbreak and recovery phases. Given that the dependent variable was a continuous variable, we used linear regression for model estimation. We used a two-way cluster-robust standard errors approach to allow for correlated errors across both dimensions of the restaurant and customer (Cameron et al. 2011).

## 6. Results and Discussion

We excluded East Asian (e.g., Japanese, Korean, and Mongolian) and Southeast Asian (e.g., Singaporean, Vietnamese, and Filipino) restaurants from non-Chinese restaurants because our pilot study showed that COVID-19 had a spillover effect on restaurants run by other Asian people (see Section D of the Online Appendix).

Table 1 reports the main results. Model (1) shows the COVID-19 impact on patronage frequency of Chinese compared to that of non-Chinese restaurants, revealing an immediate drop for Chinese restaurants during the outbreak ($\beta_2$ = -0.136, $p < 0.01$). This suggests that when COVID-19 emerged in the state, people probably attributed the spread of the virus to Chinese people and thus held a more negative attitude toward Chinese restaurants.

Moreover, $\beta_4$ of Model (1) is significantly negative ($\beta_4$ = -0.067, $p < 0.05$), suggesting that the recovery of Chinese restaurants was slower than that of non-Chinese restaurants. In the recovery phase, state governments gradually lifted lockdown restrictions and stay-at-home orders. The performance of restaurants at this juncture was more likely a result of the personal choices of customers, not government restrictions. Non-Chinese customers, in general, chose to visit Chinese restaurants less than non-Chinese restaurants. This underscores the existence of anti-Chinese racial discrimination within the restaurant industry, as reported by traditional and social media, significantly impacting business performance of Chinese restaurants. In other words, Chinese restaurants suffered from the pandemic itself, as well as from the racism associated with the pandemic. Taken together, the findings reveal that non-Chinese customers' patronage frequency of Chinese restaurants was disproportionally lower during the pandemic as compared to that of non-Chinese restaurants. Therefore, H1 is supported.

Model (2) reports the estimated effect of COVID-19 on the review rating scores of Chinese and non-Chinese restaurants. As shown in the model, there was no significant difference in customers' rating scores of Chinese restaurants and non-Chinese restaurants in the outbreak phase ($\beta_2$ = -0.009, $p$ > 0.10). However, this difference became salient in the recovery phase. The model revealed that non-Chinese customers raised their rating scores of Chinese restaurants as compared with non-Chinese restaurants in the recovery phase ($\beta_4$ = 0.055, $p$ < 0.05). This finding provides evidence of customers fighting against pandemic-driven racial discrimination. Model (3) reports the estimated effect of COVID-19 on the rating premium. Consistent with Model (2), Model (3) demonstrates that during the pandemic, as compared to non-Chinese restaurants, consumers gave higher rating premiums to Chinese restaurants in the recovery phase ($\beta_4$ = 0.075, $p$ < 0.01), but not in the outbreak phase ($\beta_2$ = -0.019, $p$ > 0.10). Thus, H2 is supported, but only for the recovery phase.

Research also shows that anti-discrimination behavior is usually manifested after racial discrimination is evinced (Bowser and Bowser 1995). Different from racial discrimination—which could have been immediately triggered by COVID-19 because of one's perceived threat (Croucher et al. 2020)—anti-discrimination is a conscious rejection of personal acts of the individual once s/he becomes cognizant of discrimination. In our context, during the outbreak phase, customers gradually learned about Chinese restaurants being racially discriminated against by observing the reduced patronage of Chinese restaurants and obtaining information from other media channels. After this, in the recovery phase, those who intended to fight such discrimination demonstrated their support for Chinese restaurants by giving higher ratings in online reviews.

Because observations were dropped in the fixed-effects estimations due to the absence of variation in the outcome variable along the fixed-effects dimension(s), we also employed non-fixed-effects estimation approaches with a comprehensive list of control variables related to restaurants and customers to retain more observations. The restaurant-related control variables included the average star rating, price level, number of rival restaurants nearby, presence/ absence of a WiFi connection at the restaurant, and noise level, as well as the availability of takeout, delivery, outdoor seating, and reservations. The customer-related control variables included the number of reviews from the customer, his/her average rating, and the number of fans of the customer. The results are reported in Models (4) to (6) of Table 1. As shown in the models, the findings were consistent with those estimated by the fixed-effects models. Descriptive statistics of the control variables and the results with all control variables are provided in the Online Appendix (see Tables A2 and A6 for details).

To further quantify the differential impacts of COVID-19, we performed the following back-of-the-envelope calculation. Compared to non-Chinese restaurants, COVID-19 led to Chinese restaurants obtaining an average of 0.127 fewer reviews per week (i.e., $e^{-0.136} - 1$) in the outbreak phase and 0.065 fewer reviews per week (i.e., $e^{-0.067} - 1$) in the recovery phase. The significant difference in the customer patronage of Chinese and non-Chinese restaurants represents a large revenue distinction between them. We estimated that the revenue gap between Chinese and non-Chinese restaurants in the outbreak and recovery phase respectively accounted for 41.9% and 21.5% of the revenue before the pandemic, thus demonstrating considerable differential impacts of COVID-19.

**Table 1. The impacts of COVID-19 on the patronage frequency and review rating.**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Patronage | Rating | Premium in rating | Patronage | Rating | Premium in rating |
| *Chinese* | | | | 0.131** | -0.005 | -0.012 |
| | | | | (0.036) | (0.013) | (0.011) |
| *Outbreak* | 0.021† | 0.004 | 0.016 | 0.052** | -0.001 | 0.009 |
| | (0.012) | (0.019) | (0.017) | (0.016) | (0.011) | (0.010) |
| ***Chinese × Outbreak*** | **-0.136**** | **-0.009** | **-0.019** | **-0.147**** | **0.041** | **0.027** |
| | **(0.033)** | **(0.038)** | **(0.034)** | **(0.036)** | **(0.026)** | **(0.024)** |
| *Recovery* | -0.533** | 0.062** | 0.088** | -0.565** | 0.054** | 0.074** |
| | (0.011) | (0.014) | (0.013) | (0.011) | (0.008) | (0.007) |
| ***Chinese × Recovery*** | **-0.067*** | **0.059*** | **0.075**** | **-0.066*** | **0.057**** | **0.038*** |
| | **(0.029)** | **(0.026)** | **(0.022)** | **(0.029)** | **(0.018)** | **(0.015)** |

| | | | | | | |
|---|---|---|---|---|---|---|
| *Constant* | -0.427** | 3.911** | -0.510** | -4.967** | -1.960** | -2.860** |
| | (0.005) | (0.007) | (0.006) | (0.084) | (0.022) | (0.022) |
| Monthly FE | √ | √ | √ | √ | √ | √ |
| Restaurant FE | √ | √ | √ | | | |
| Customer FE | | √ | √ | | | |
| Restaurant-related controls | | | | √ | √ | √ |
| Customer-related controls | | | | | √ | √ |
| Observations | 1,389,372 | 204,489 | 204,489 | 1,578,912 | 346,759 | 346,759 |
| No. of restaurants | 27,212 | 20,148 | 20,148 | 30,956 | 27,210 | 27,210 |
| No. of customers | | 52,960 | 52,960 | | 190,502 | 190,502 |
| $R^2$ | 0.263 | 0.617 | 0.500 | 0.128 | 0.458 | 0.158 |

Notes: Robust standard errors are reported in parentheses; ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$.

## 7. Supplementary Analyses

### 7.1 Alternative Measures of Anti-Discrimination

In addition to the rating and premium in rating, we also constructed two alternative measures predominantly led by anti-discrimination. This was achieved by applying text mining techniques to consumer reviews to validate the robustness of the results. The qualitative assessment of consumer reviews also indicated that, in occasional cases, customers also expressed their support for restaurants explicitly in their reviews. Among these, some offered general support for local restaurants (e.g., *"…trying to support local during the COVID-19…"* and "*…it's going to be with local businesses…*"), but others affirmed support for Chinese restaurants specifically (e.g., *"…we are huge fans of China…we lived in China for two years…"*, and *"…difficult times for Chinese restaurants…Please consider visiting them during the COVID-19 crisis…"*). Based on these observations, we utilized text mining and machine learning techniques to identify evidence of both *general support* for all local restaurants and *specific support* for local Chinese restaurants from the review text. The manual labeling and machine learning procedures are detailed in Online Appendix Section E.

For general support, we replaced the dependent variable of specification (2) with *general support* and focused on the coefficients of $Chinese_i \times Outbreak_{it}$ and $Chinese_i \times Recovery_{it}$, which quantify whether Chinese restaurants received more general support after the pandemic. Regarding specific support for Chinese restaurants, we restricted our sample to reviews of Chinese restaurants only and estimated the change in *specific support for Chinese* in both the outbreak and recovery phases (the interaction terms were thus excluded from specification (2)). The coefficients of $Outbreak_{it}$ and

$Recovery_{it}$ represent whether the incidence of Chinese-specific support expressed in the review text increased after COVID-19.

Table 2 reports the results. Models (1) and (2) present the results for general support, and Models (3) and (4) report the results for specific support for Chinese restaurants. As shown in Model (1), Chinese restaurants received more general support after COVID-19, but only in the recovery phase ($\beta_2$ = -0.015, $p > 0.10$; $\beta_4 = 0.012$, $p < 0.01$). Model (3) reveals that there was an increase in the specific support for Chinese restaurants (which was explicitly expressed in the review text) after the COVID-19 outbreak. However, consistent with our previous results, the increase was only significant in the recovery phase ($\beta_3 = 0.029$, $p < 0.05$), not in the outbreak phase ($\beta_1 = 0.008$, $p > 0.10$). In Models (2) and (4), we used a comprehensive list of restaurant- and customer-related control variables—instead of two-way fixed effects—and found that the findings were similar to those of Models (1) and (3). This set of results aligns with our main finding, namely that customers might have needed time to recognize racial discrimination toward Chinese restaurants and then act consciously against it.

**Table 2. Alternative measures of anti-discrimination.**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Sample | All restaurants | | Chinese restaurants | |
| | General support | General support | Specific support for Chinese restaurants | Specific support for Chinese restaurants |
| *Chinese* | | 0.046** | | |
| | | (0.005) | | |
| *Outbreak* | 0.001 | 0.003 | **0.008** | **-0.003** |
| | (0.005) | (0.004) | **(0.015)** | **(0.007)** |
| ***Chinese × Outbreak*** | **-0.015** | **0.001** | | |
| | **(0.014)** | **(0.011)** | | |
| *Recovery* | 0.000 | 0.000 | **0.029*** | **0.009*** |
| | (0.000) | (0.000) | **(0.013)** | **(0.004)** |
| ***Chinese × Recovery*** | **0.012**** | **0.012**** | | |
| | **(0.004)** | **(0.003)** | | |
| *Constant* | 0.140** | 0.232** | 0.056** | -0.028 |
| | (0.002) | (0.008) | (0.006) | (0.020) |
| Monthly FE | √ | √ | √ | √ |
| Restaurant FE | √ | | √ | |
| Customer FE | √ | | √ | |
| Restaurant-related controls | | √ | | √ |
| Customer-related controls | | √ | | √ |
| Observations | 204,489 | 346,759 | 6,471 | 24,013 |
| No. of restaurants | 20,148 | 27,210 | 1,145 | 2,279 |
| No. of customers | 52,960 | 190,502 | 2,383 | 19,373 |
| $R^2$ | 0.514 | 0.013 | 0.582 | 0.008 |

Notes: Robust standard errors are reported in parentheses; ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$. To retain more observations, fixed-effects linear regression was employed for estimation.

### 7.2 Heterogeneity of Local Racial Tension

We further investigated how the local social environment (i.e., racial tension in the local community) shaped people's expressions of racial discrimination and acts of anti-discrimination. We focused on two variables that measured the intensity of racial tension in the city where customers lived. The first variable was the *percentage of Chinese people among the city's population.*[8] Theoretically, its moderating effects on the impact of COVID-19 have competing predictions. On one hand, the presence of more Chinese people in the city might possibly raise race salience and make the threat perceived by non-Chinese people more pronounced (Maeder and Ewanation 2018). If so, this would conceivably amplify the impact of COVID-19 on discrimination against Chinese people (per ITT). On the other hand, more Chinese people in the city would likely augment the probability of non-Chinese people having contact with Chinese people; if so, this may have mitigated discrimination against Chinese people (per ICT). However, such interactions may not always be positive and meaningful (Vonofako et al. 2007). In this case, the mitigation of discrimination would be limited.

There are also competing predictions regarding anti-discrimination. On one hand, a higher percentage of Chinese people in the city might diminish the perception of their minority status, thereby reducing empathy toward Chinese people and the subsequent anti-discrimination acts of non-Chinese people. On the other hand, potentially more intergroup contact between Chinese and non-Chinese people—though it may not always be positive and meaningful—may well facilitate the undertaking of anti-discrimination behaviors.

The second variable was the *incidence rate of anti-Asian crimes among the local population*,[9] which was measured as the average number of anti-Asian crimes per million people from 2000 to 2019. This variable indicates the city's degree of racial discrimination and potentially deeply rooted racial bias. Theoretically, Chinese people would probably encounter more racial discrimination and receive less anti-discrimination support in cities with a higher degree of anti-Asian crime.

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[8] The data were obtained from the American Community Survey (https://www.census.gov/programs-surveys/acs) and United Nations data (http://data.un.org/).

[9] The data were obtained from the FBI (https://ucr.fbi.gov/hate-crime). Given that there were no available data regarding anti-Chinese crimes, the incidence rate of anti-Asian crimes best proxies the level of racial tension between Chinese and non-Chinese people based on all the accessible data sources.

Fortunately, we had a representative sample with considerable variation in demographics to conduct this set of analyses. To estimate the heterogeneity effects of local racial tension, we integrated a third difference (i.e., the measure of local racial tension) into the DID framework to construct a difference-in-difference-in-differences (DDD) model. The model specifications were as follows:

$$\begin{aligned} Y_{it} = \alpha_i + \delta_t + \beta_1 \cdot Outbreak_{it} + \beta_2 \cdot Chinese_i \times Outbreak_{it} + \beta_3 \cdot Outbreak_{it} \times z_i + \beta_4 \cdot Chinese_i \times Outbreak_{it} \times z_i \\ + \beta_5 \cdot Recovery_{it} + \beta_6 \cdot Chinese_i \times Recovery_{it} + \beta_7 \cdot Recovery_{it} \times z_i + \beta_8 \cdot Chinese_i \times Recovery_{it} \times z_i + \varepsilon_{it} \end{aligned}, \quad (3)$$

$$\begin{aligned} Y_{ijt} = \alpha_i + \theta_j + \delta_t + \beta_1 \cdot Outbreak_{it} + \beta_2 \cdot Chinese_i \times Outbreak_{it} + \beta_3 \cdot Outbreak_{it} \times z_i + \beta_4 \cdot Chinese_i \times Outbreak_{it} \times z_i \\ + \beta_5 \cdot Recovery_{it} + \beta_6 \cdot Chinese_i \times Recovery_{it} + \beta_7 \cdot Recovery_{it} \times z_i + \beta_8 \cdot Chinese_i \times Recovery_{it} \times z_i + \varepsilon_{ijt} \end{aligned}, \quad (4)$$

where specification (3) is the analysis of customer patronage frequency at the restaurant-week level, and specification (4) is the analysis of the rating and rating premium at the review level. With other variables remaining the same in terms of their definitions, $z_i$ refers to the percentage of Chinese people in the city where restaurant *i* is located, or the incidence rate of anti-Asian crimes in the city where restaurant *i* is located. Of primary interest were $\beta_4$ and $\beta_8$, which capture the moderating effects of the intensity of racial tension in the city.

Table 3 presents the DDD estimation results. Models (1) to (3) reveal the moderating role of the percentage of Chinese people, whereas Models (4) to (6) show the moderating role of the incidence rate of anti-Asian crimes. As shown in Model (1), a higher percentage of Chinese people in the city further reduced the customer patronage frequency of Chinese restaurants in both the outbreak phase ($\beta_4$ = -0.054, $p < 0.05$) and the recovery phase ($\beta_8$ = -0.084, $p < 0.01$). The negative effect emerging immediately in the outbreak phase suggests that greater Chinese presence raised race salience (Maeder and Ewanation 2018). As mentioned in the theoretical background, because the Chinese community was deemed a threat to people's physical well-being during the COVID-19 pandemic (Binder 2020), the increased Chinese race salience led to more racial discrimination toward Chinese people.

Models (2) and (3) show that more Chinese people living in the city discouraged customers from giving higher evaluations of Chinese restaurants, but only in the recovery phase ($\beta_4$ = -0.009, $p > 0.10$; $\beta_8$ = -0.070, $p < 0.01$ in Model (2) for *rating*; $\beta_4$ = -0.063, $p > 0.10$; $\beta_8$ = -0.050, $p < 0.05$ in Model (3) for *rating premium*). Despite the possibility that the presence of more Chinese people in the city would have facilitated contact between Chinese and non-Chinese people, the findings suggest that the contact might not have been meaningful in general. Moreover, greater Chinese presence may decrease people's perceptions of them as a minority group, thus impairing their motivation to take action against discrimination and support Chinese people and restaurants (Bonnett, 2005). Compared with this set of results, our main results reported in Section 6 imply that having meals in Chinese restaurants is an opportunity for non-Chinese people to experience Chinese culture, which tends to foster meaningful contact and motivate them to undertake anti-discrimination behavior.

In Model (4), the marginally significant $\beta_8$ ($\beta_8$ = -0.066, $p < 0.10$) demonstrates the trend of more severe discrimination toward Chinese people occurring in cities with a higher incidence rate of anti-Asian crimes during the pandemic. However, Models (5) and (6) suggest that the evaluations of Chinese restaurants did not differ significantly across cities with various incidence rates of anti-Asian crimes ($\beta_4$ = 0.009, $p > 0.10$; $\beta_8$ = -0.006, $p > 0.10$ in Model (5) for *rating*; $\beta_4$ = 0.002, $p > 0.10$; $\beta_8$ = 0.001, $p > 0.10$ in Model (6) for *rating premium*). Instead of the predicted negative impact of anti-Asian crime rates, the non-significant findings might be because, for individuals against racial discrimination, more anti-Asian crimes in the city could have enhanced their empathy toward Chinese people and evoked anti-discrimination behavior (Cuff et al. 2016). This, in turn, may have compensated for the negative effect of anti-Asian crime rates in the city.

**Table 3. The heterogeneity of local racial tension.**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Patronage | Rating | Premium in rating | Patronage | Rating | Premium in rating |
| | *z* is the % of Chinese people | | | *z* is the incidence of anti-Asian crimes | | |
| ***Chinese × Outbreak × z*** | **-0.054*** | **-0.009** | **-0.063** | **-0.043** | **0.009** | **0.002** |
| | **(0.027)** | **(0.047)** | **(0.042)** | **(0.031)** | **(0.006)** | **(0.005)** |
| ***Chinese × Recovery × z*** | **-0.084**** | **-0.070**** | **-0.050*** | **-0.066†** | **0.006** | **0.001** |
| | **(0.020)** | **(0.026)** | **(0.023)** | **(0.037)** | **(0.004)** | **(0.004)** |
| *Constant* | -0.430** | 3.912** | -0.509** | -0.582** | 3.932** | -0.499** |
| | (0.005) | (0.007) | (0.006) | (0.012) | (0.008) | (0.007) |
| *Outbreak, Recovery, z × (Outbreak, Recovery, Chinese)*[a] | Added | Added | Added | Added | Added | Added |
| Monthly FE | √ | √ | √ | √ | √ | √ |
| Restaurant FE | √ | √ | √ | √ | √ | √ |
| Customer FE | | √ | √ | | √ | √ |
| Observations | 1,389,372 | 204,489 | 204,489 | 1,105,887 | 178,219 | 178,219 |
| No. of restaurants | 27,212 | 20,148 | 20,148 | 21,936 | 16,703 | 16,703 |
| No. of customers | | 52,960 | 52,960 | | 47,287 | 47,287 |
| $R^2$ | 0.263 | 0.617 | 0.500 | 0.261 | 0.617 | 0.498 |

Notes: Robust standard errors are reported in parentheses; ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$. The results of non-fixed-effects estimations obtained by including restaurant- and customer-related control variables are available upon request.

[a] The coefficients for *Outbreak*, *Recovery*, *Outbreak*×*z*, *Recovery*×*z*, and *Chinese*×*z* are presented in Table A8 due to the page limit.

### 7.3 Mechanism Tests of Anti-Discrimination

In Section 7.2, we found that the presence of more Chinese people in the surrounding area- which was supposed to increase intergroup contacts- did not evoke more anti-discrimination behavior. According to ICT, people's empathy toward out-groups will be induced only when the contact is meaningful and positive, thus leading individuals to take action against anti-discrimination (Vonofako et al. 2007). Therefore, we further tested whether meaningful contacts served as the mechanism underlying anti-discrimination. We defined a new indicator variable, namely $Repeat\_Customer_j$, which was set to one if customer $j$ patronized Chinese restaurants more than non-Chinese restaurants before the COVID-19 outbreak, and zero otherwise. Repeat customers who patronized Chinese restaurants frequently were prone to have more meaningful contact with Chinese people.

We then replaced $z$ in specification (4) with $Repeat\_Customer_j$ and re-estimated the model. Table A9 presents the results. As shown in Models (1) and (2), repeat customers of Chinese restaurants exhibited more anti-discrimination behaviors than infrequent customers in the recovery phase ($\beta_8$ = 0.366, $p < 0.05$ in Model (1) for *rating*; $\beta_8$ = 0.253, $p < 0.10$ in Model (2) for *rating premium*). Consistent with other studies (e.g., Selvanathan et al. 2018), these findings confirm the argument of ICT, namely that positive and meaningful intergroup contact, rather than general contact, plays an important role in facilitating anti-discrimination behaviors (Pettigrew 1998).

## 8. Robustness Checks, Sensitivity Analysis, and Falsification Tests

### 8.1 Analyses Using Foot Traffic Data

To test the robustness of our findings with alternative data, we utilized a dataset released from SafeGraph to repeat our analyses of discrimination (Li and Wang 2020, de Vaan et al. 2021). The SafeGraph dataset aggregates location data from numerous applications on mobile devices to provide foot traffic patterns at physical places. The dataset covers 47 states in the U.S. For each restaurant, we observed its weekly number of visits, weekly number of visitors, category, visit duration, geographic location, North American Industry Classification System (NAICS) industry code, and name of the branded chain if pertinent. In addition, the dataset included weekly sales data of a subsample of restaurants (not all of them). We used the category to determine whether a given restaurant was a Chinese one. The summary statistics are shown in Table 4. About 5.5% of all restaurants in the dataset were Chinese restaurants. The average number of visits and visitors each week were 62.5 and 49.7, respectively, and the average sales each week were $718.6.

**Table 4. The summary statistics of the SafeGraph data.**

| Variable | Obs. | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| *Chinese* | 280,447 | .055 | .228 | 0 | 1 |
| *num_visit* | 280,447 | 62.494 | 94.852 | 1 | 4,475 |
| *num_visitor* | 280,447 | 49.724 | 74.307 | 1 | 4,307 |
| *sales* | 139,052 | 718.576 | 1,248.648 | 0 | 30,392.381 |
| Visit duration: shorter than 5 min | 280,447 | 2.277 | 4.315 | 0 | 140 |
| Visit duration: 5-10 min | 280,447 | 19.331 | 36.736 | 0 | 896 |
| Visit duration: 11-20 min | 280,447 | 8.863 | 16.117 | 0 | 726 |
| Visit duration: 21-60 min | 280,447 | 15.654 | 27.509 | 0 | 1,669 |
| Visit duration: 61-120 min | 280,447 | 7.073 | 15.907 | 0 | 961 |
| Visit duration: 121-240 min | 280,447 | 4.139 | 10.503 | 0 | 544 |
| Visit duration: longer than 240 min | 280,447 | 5.157 | 16.145 | 0 | 1,853 |

We then used the SafeGraph dataset to re-run the analysis of discrimination.

$$Y_{it} = \alpha_i + \delta_t + \beta_1 \cdot Outbreak_{it} + \beta_2 \cdot Chinese_i \times Outbreak_{it} + \beta_3 \cdot Recovery_{it} + \beta_4 \cdot Chinese_i \times Recovery_{it} + \varepsilon_{it}, \quad (5)$$

where *i* and *t* represent the restaurant and week, respectively. We had three main dependent variables: (1) *num_visit*, the weekly count of visits to each restaurant; (2) *num_visitor*, the weekly number of visitors to each restaurant; (3) sales, the weekly sales of each restaurant. Unlike the dependent variables in our main analysis described in Section 5.2, here, we could not distinguish how many visits were made by non-Chinese customers. The results, therefore, represent the difference in business performance driven by both non-Chinese and Chinese customers. Considering that the Yelp data indicated that about 96% of customers were non-Chinese customers, the dependent variables used here mostly reflect the behaviors of non-Chinese customers.

As shown in Table 5, the numbers of visits and visitors and the sales of Chinese restaurants decreased more after COVID-19 as compared to those of non-Chinese restaurants. This was consistent with our main findings. This analysis also validates the utilization of the number of reviews as a measure of restaurant performance in the main analysis in Section 5.2.

**Table 5. The results of analyses using SafeGraph data**

| | (1)<br>*num_visit* | (2)<br>*num_visitor* | (3)<br>*sales* |
|---|---|---|---|
| *Outbreak* | 0.028†<br>(0.017) | 0.028*<br>(0.014) | 0.050**<br>(0.016) |

| | | | |
|---|---|---|---|
| ***Chinese × Outbreak*** | **-0.027** | **-0.037** | **-0.122**** |
| | **(0.027)** | **(0.027)** | **(0.040)** |
| *Recovery* | 0.197 | 0.345† | -0.848** |
| | (0.275) | (0.179) | (0.025) |
| ***Chinese × Recovery*** | **-0.098**** | **-0.112**** | **-0.146**** |
| | **(0.031)** | **(0.031)** | **(0.042)** |
| *Constant* | 4.591** | 4.303** | 7.709** |
| | (0.130) | (0.085) | (0.013) |
| Monthly FE | √ | √ | √ |
| Restaurant FE | √ | √ | √ |
| Observations | 280,416 | 280,416 | 139,039 |
| $R^2$ | 0.812 | 0.814 | 0.850 |

*Notes*: Robust standard errors are reported in parentheses; ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$.

### 8.2 Online Controlled Experiments

To further check the robustness of our findings and test whether a perceived threat and the awareness of racial discrimination serve as mechanisms, we ran two online controlled experiments. Specifically, Experiment 1 sought to support the racial discrimination hypothesis (H1). We found that COVID-19, not other diseases, triggered American's perceived threat from the Chinese as a group; this increased discrimination toward Chinese restaurants, which manifested as reduced customer patronage.

Experiment 2 sought to support the anti-discrimination hypothesis (H2). We found that the salience of discrimination toward Chinese restaurants after the emergence of the pandemic triggered participants' anti-discrimination toward Chinese restaurants, manifested as increased positive comments. Details of these two experiments are reported in Section A of the Online Appendix.

### 8.3 Further Robustness Checks, Sensitivity Analysis, and Falsification Tests

We further conducted a series of tests to validate the robustness of our results. First, to examine the effect of COVID-19 over time and validate the parallel trend assumption for the DID analysis, we employed a relative time model with the lead and lag periods as an alternative model. Second, we used alternative estimators (i.e., a zero-inflated model) to validate our findings. Third, we ruled out more alternative explanations of the systematic differences between Chinese and non-Chinese restaurants. Fourth, we conducted a sensitivity analysis using different settings of the outbreak and recovery phases. Finally, we carried out falsification tests to confirm that our results were not due to coincidence. Table 6 summarizes the descriptions of these tests; however, due to the page limits, the Supplementary Text of the Online Appendix offers enhanced details.

**Table 6. The summary of robustness checks, sensitivity analysis, and falsification tests.**

| **Concern** | **Test** | **Description** | **Outcome** | **Location** |
|---|---|---|---|---|
| | | **Alternative Models** | | |
| Validity of the parallel trend assumption | Relative time model with lead and lag periods | In the relative time model, we included a set of time dummies indicating the chronological distance of an observation period with respect to the COVID-19 outbreak. | The coefficients for the pre-outbreak dummies were not significant. | ST F1 Table A10 |
| Excessive zeros of the number of reviews | Zero-inflated model | In the zero-inflated model, we modeled whether a customer's visit to a restaurant depended on the number of COVID-19 cases reported. | The results were consistent with the main findings. | ST F2 Table A11 |
| | | **Alternative Explanations** | | |
| The "quality" of restaurants was altered by COVID-19 | Control for quality score | We used the word2vec technique to characterize four dimensions of restaurant quality (i.e., cleanliness, taste, service, and environment). | The results were consistent with the main findings after controlling for the quality scores. | ST G1 Table A12 |
| Restaurants took different COVID-19 precautions | Control for COVID-19 precaution measures | We used the word2vec technique to measure the COVID-19 precautions by using the words "COVID-19 precaution," "mask," "glove," and "sanitizer." | The results were consistent with the main findings after controlling for the COVID-19 precaution level. | ST G2 Table A12 |
| Chinese restaurants offered fewer promotions during COVID-19 | Examine the change in promotions during COVID-19 | We used the word2vec technique to identify whether a focal review contained words reflecting a price discount. | There was no significant difference between Chinese and non-Chinese restaurants in terms of price promotions before and after COVID-19. | ST G3 Table A13 |
| Chinese restaurants had been closed more often for a longer amount of time during COVID-19 | Identify closure time using SafeGraph data | We used the SafeGraph data to identify the (1) permanent closure and (2) temporary closure of restaurants. | The results were consistent with the main findings when we excluded data from closed dates. | ST G4 Table A14 |
| More consumers of Chinese restaurants chose take-out service during COVID-19 | Distinguish take-out and dine-in visits using SafeGraph data | We defined visits lasting longer than 20 min and shorter than 1 h as dine-in visits | The results were consistent with the main findings when we only included dine-in visits. | ST G5 Table A15 |
| The rating gap was driven by customers' self-selection | Conduct subsample analyses and use matching methods to create comparable samples | (1) We conducted subsample analyses of those who patronized restaurants before and after COVID-19.<br>(2) We paired post-COVID-19 Chinese restaurant reviewers with closely matched reviewers of non-Chinese restaurants.<br>(3) We simulated potential post-COVID-19 ratings given by customers who did not patronize Chinese restaurants after COVID-19.<br>(4) We created a "selected" control group to make it comparable to the treatment group.<br>(5) We used customers visiting three types of restaurants (American, African and fast-food restaurants) before and after COVID-19 as control groups and conducted DID analyses. | The results were consistent with the main findings. | ST G6 Table A16 |

| | | | | |
|---|---|---|---|---|
| Differences in information, resources, and regulations between chain and independent restaurants in responding to COVID-19 | Compare chain restaurants and independent restaurants | (1) We matched restaurants by their names and identified chain restaurants if two or more restaurants had the exact same name.<br>(2) We treated the number of restaurants with the same name as a scale of the chain of restaurants.<br>(3) We examined the heterogeneity in the effects on chain restaurants and independent restaurants. | There was no significant difference between the reported effects on chain restaurants and independent restaurants | ST G7<br>Table A17 |
| The patronage change of non-Chinese restaurants may have been subject to competition with nearby Chinese restaurants | Compare Chinese restaurants and counterparts with similar business attributes | We excluded non-Chinese restaurants that were in proximity to Chinese restaurants (i.e., within 3 km) from our control group. We then re-conducted the matching based on business attributes. | The results were consistent with the main findings based on the newly matched sample. | ST G8<br>Table A18 |
| Chinese restaurants might have been confronted with supply chain shortages during COVID-19 | Examine trade between the U.S. and China | We compared both the imports and exports from/to China before and after COVID-19 based on U.S. Census Bureau data. | Both the imports and exports from/to China increased significantly after the outbreak of COVID-19. | ST G9<br>Table A19 |
| **Sensitivity Analysis** | | | | |
| Whether the effect was subject to the defined COVID-19 phases | Sensitivity analyses | We re-estimated the models based on different definitions of COVID-19 phases. | The results were consistent with the main findings. | ST H<br>Table A20 |
| **Falsification Tests** | | | | |
| If the effect was due to racial discrimination against Chinese people, it should not have existed in other ethnic restaurants | Falsification test on Latino restaurants | We conducted an analysis to compare Latino restaurants and non-Latino restaurants. | There was no significant difference in terms of the patronage frequency or ratings. | ST I1<br>Table A21 |
| If the effect was because of COVID-19, it should not have existed in 2019 | Falsification test on data from 2019 | We conducted an analysis based on a pseudo-outbreak date (i.e., the same time in the previous year as the pseudo date of the "COVID-19 outbreak"). | There was no effect of the pseudo-outbreak on the patronage frequency or ratings. | ST I2<br>Table A22 |
| Whether there was review bombing | Use more detailed dependent variables and conduct text mining | We separately tested whether positive and negative reviews increased. Moreover, we used text mining to look for racist reviews. | There was no evidence of review bombing. | ST K<br>Table A23 |
| Whether the VADER package used in the sentiment analysis is robust | Use alternative packages | We employed two commonly used alternative packages (TextBlob and AFINN) to conduct sentiment analysis. We provided examples that mapped *premium_in_rating* to *rating* with review text. | The results are consistent with the main findings. | ST L<br>Tables A24 and A25 |

**Note*: ST denotes the Supplementary Text in the Online Appendix.

## 9. Conclusions

The seemingly unceasing racial discrimination and violence directed against Asians—especially Chinese people—became especially prevalent at the outset of the COVID-19 pandemic. Much of it was a function of disinformation disseminated in traditional and social media. By utilizing a dataset from the largest online review website in the U.S. and Canada, namely Yelp.com, and employing the DID approach, we compared the performance of Chinese restaurants relative to non-Chinese restaurants at different phases of the pandemic. We found evidence of racial discrimination, as manifested in the decreased frequency of the patronage of Chinese restaurants as compared with non-Chinese restaurants. We also discovered that increased racial discrimination triggered appropriate anti-discrimination actions to counter the harmful effects of racial discrimination. Customers who continued to patronize Chinese restaurants after the COVID-19 outbreak chose to fight racial discrimination by giving higher rating scores to Chinese restaurants than did their counterparts who did not undertake such behaviors.

**9.1 Theoretical Contributions**

By examining how racial discrimination is reflected in the restaurant context, we linked the significant literature on racial discrimination in the marketplace (Davis 2018, Kuppuswamy and Younkin 2020, Younkin and Kuppuswamy 2018) to a body of research that has investigated business performance. Prior literature on marketplace discrimination has mainly focused on B2C and P2P discrimination (e.g., Blair et al. 2013, Ge et al. 2020, Gunarathne et al. 2022, Penner et al. 2010, Younkin and Kuppuswamy 2018). We contribute to this stream of work by taking a unique economic perspective to examine a largely ignored phenomenon, namely consumers' racial discrimination against businesses operated by ethnic minorities (i.e., C2B racial discrimination) during the pandemic. To the best of our knowledge, our research represents one of the first novel explorations of C2B racial discrimination within the marketplace. It also constitutes an initial attempt to explore how the racial discrimination resulting from the COVID-19 pandemic influenced the attitudes of customers toward organizations, and thus impacted organization performance. Moreover, C2B discrimination—compared to B2C and P2P discrimination—tends to be more hidden and undiscoverable; thus, there has been a dearth of empirical research on this topic. We investigated a subtle but more factual form of racial discrimination manifested as the customer patronage of Chinese restaurants.

Second, our finding that growing racial discrimination was mainly reflected in the significantly decreased patronage frequency of Chinese restaurants provides new insights into how racial discrimination can be manifested in a business context. Furthermore, this research is one of the early efforts to identify anti-discrimination behaviors in a business context. Our results indicate that customers tended to give disproportionately higher ratings to Chinese restaurants during the COVID-19 pandemic, which reveals how individuals could be strategic and react positively when becoming cognizant of racial discrimination in the marketplace.

Third, we contribute to the emerging literature examining the consequences of epidemic diseases (Croucher et al. 2020, Wang et al. 2021) by extending the research scope to customers' attitudes toward businesses. We revealed that COVID-19 had different impacts on businesses in different phases of the pandemic. Specifically, we demonstrated that COVID-19 not only changed the patronage frequency (a manifestation of racial discrimination), but also influenced evaluations on an online review site (a manifestation of anti-discrimination).

Fourth, we contribute to the emerging literature on the efficacy of online reviews (Saifee et al. 2020; Zhu and Zhang 2010). For example, prior research has revealed that the type of product influences the effectiveness of online reviews. Specifically, empirical research on experience and search goods has generally found online reviews to be effective (Zhu and Zhang 2010). However, Saifee et al. (2020) found that online reviews of physicians (i.e., credence goods) may not be reliable indicators of clinical outcomes, such as emergency room visits and readmission risk. We hence extend this stream of scholarship by demonstrating that people's racial attitudes can also bias their review comments in the restaurant context.

Finally, we contribute to the stream of literature on ITT and ICT by applying the theories to the pandemic-related discrimination context. Specifically, we respond to the call for the further development of ITT in different contexts (Harrison and Peacock 2010). Extending the prior literature on ITT—which has mainly focused on attitudes toward immigrants (Stephan et al. 2000)—the present work examined how discrimination toward Chinese people manifested in the Chinese restaurant context. Moreover, we found that consumers who patronized Chinese restaurants before the pandemic were more likely to take anti-discrimination actions to support Chinese restaurants. This answers the call for further investigations into how to maneuver more prejudiced individuals into contact situations to improve intergroup relationships (Crisp and Turner 2013).

### 9.2 Managerial Implications

This study provides managerial implications for policymakers, restaurant owners, and platform managers. First, we revealed that public crises could trigger serious racial discrimination toward minority groups. This discrimination represents a “pandemic on a pandemic” for some groups (i.e., Chinese restaurants in the present study). Moreover, some discrimination is subtle and hard to detect (i.e., consumers’ reduced patronage frequency of Chinese restaurants in the present study). Therefore, government policymakers should be prepared for the emergence or increased presence of racial discrimination during a public crisis. Governments, business entities, and citizens must work together to combat such discrimination. Our findings endorse the appearance of politicians in Chinese restaurants to encourage people to patronize them more.[10] Moreover, U.S. Congress approved a plan to replenish the federal government's Paycheck Protection Program fund for small businesses, and our analysis suggests that some of these funds should be directed toward small minority-owned businesses, as they face additional race-related challenges.

Second, consistent with prior research, our findings revealed that interracial interactions could trigger anti-discrimination behaviors. This was manifested as customers, especially repeat customers of Chinese restaurants, providing positive comments about Chinese restaurants on Yelp. Therefore, policymakers must attach importance to interracial contact and dialogue as an effective method to combat racial discrimination.

Third, we revealed that some customers endeavored to offer support to Chinese restaurants by deliberately giving them higher rating scores. These higher ratings can improve a Chinese restaurant’s attractiveness to potential customers, thereby helping that business in the longer term. However, these high ratings might have generated bias in the reviews, as they may not have accurately reflected the true quality of a given restaurant. Accordingly, online review platforms would be well advised to exercise caution in light of this finding, possibly by adjusting the ratings with a COVID-19 factor.

[10] Nancy Pelosi visits San Francisco's Chinatown amid Coronavirus concerns. *NBC Bay Area* (February 24), https://www.nbcbayarea.com/news/local/nancy-pelosi-visits-san-franciscos-chinatown/2240247/. Boston Mayor Marty Walsh tries to dispel Coronavirus fears with Chinatown lunch. *WBUR* (February 18), https://www.wbur.org/bostonomix/2020/02/18/boston-marty-walsh-chinatown-lunch-coronavirus.

Individual users who read reviews and act based on them should be made aware of possible bias and urged to pay keen attention to the review text, rather than simply relying on the rating.

**9.3 Limitations**

This study was characterized by certain limitations suggestive of future research avenues. First, we used the patronage frequency of customers as a proxy for racial discrimination. Because racial discrimination is well-recognized as being subtle and insidious, it can usually be difficult to capture (e.g., Price and Wolfers 2010). This study offered an early attempt to glean individuals' racial discrimination in a C2B context. We also conducted controlled experiments to validate the relationship between customer patronage and racial discrimination in the context of COVID-19. Future research may build on our study and develop more refined measures for the identification of racial discrimination in people's daily life.

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**Online Appendix for**

# Racial Discrimination and Anti-Discrimination: Impact of the COVID-19 Pandemic on Chinese Restaurants in North America

This file includes the following:

Supplementary Text Sections A to L

Tables A1 to A25

Figure A1

**Supplementary text**

**A. Experimental Evidence**

**A1. Experiment 1: Discrimination towards Chinese Restaurants**

Experiment 1 sought to support the racial discrimination hypothesis (H1) in an experimental setting. To this end, we first measured participants' perceived threat from the Chinese and attitudes towards Chinese restaurants in 2019 (i.e., pre-COVID-19). Then we randomly assigned participants to one of the two epidemic conditions (i.e., COVID-19 vs. other disease) and measured their perceived threat from the Chinese and attitudes towards Chinese restaurants again (i.e., during-COVID-19). We used norovirus as a control condition, as this virus happened to occur at a similar time to COVID-19 and was not associated with anti-Chinese sentiment (*USAToday* 2020). We expected that COVID-19—not the norovirus—would trigger Americans' perceived threat from the Chinese group. This would lead to increased discrimination towards Chinese restaurants, manifesting as reduced patronage frequency for Chinese restaurants instead of increased negative comments.

**Method**. We conducted the experiment on Amazon's Mechanical Turk (MTurk). Only non-Asian participants who were born in the U.S., were living in the U.S., and were U.S. citizens could participate. A total of 202 participants ($M_{age}$ = 42.65; 54.0% female) took part in this experiment for a small payment. They were randomly assigned to one of two (i.e., COVID-19 vs. norovirus) epidemic conditions.

First, all participants were asked to imagine that the time now was 2019. They were asked to recall their life in 2019 and answer questions based on their life in 2019. Specifically, we first measured participants' patronage frequency (i.e., *"How likely are you to patronize a Chinese restaurant?" 1 = not likely at all; 7 = very likely*) and attitude towards Chinese restaurants (i.e., *"How likely are you to write a negative comment for a Chinese restaurant on Yelp?" 1 = not likely at all; 7 = very likely*). Then we measured perceived threat from Chinese people based on ITT using a six-item scale from Stephan et al. (1998) (i.e., *"American identity is threatened because there are too many Chinese today," 1 = strongly disagree; 7 = strongly agree*).

Participants were then randomly assigned to one of two (i.e., COVID-19 vs. norovirus) epidemic conditions. Participants in the COVID-19 virus condition read a newspaper article titled, "*When did the coronavirus start spreading in the U.S.? Likely in January, CDC analysis suggests*" (adapted from Branswell 2020).After reading the article, participants were asked to summarize the main idea expressed in it. Then they were asked to imagine that the time now was the summer of 2020, and COVID-19 was still circulating in the U.S. They needed to imagine their life during the epidemic in 2020 and answer questions regarding patronage frequency and attitude towards Chinese restaurants, as well as their perceived threat from the Chinese. All measures were the same as the first part above.

Similarly, participants in the norovirus condition read a newspaper article titled, "*At least 200 people sick after norovirus outbreak at Louisiana casino, health officials say*" (adapted from *USAToday* 2020). Participants then summarized the main idea expressed in the article. Then participants were asked to imagine that the time now was the summer of 2020, and the norovirus was still circulating in the U.S. They needed to imagine their life during the norovirus pandemic in 2020 and answer questions regarding patronage frequency and attitude towards Chinese restaurants, as well as their perceived threat from the Chinese.

**Results**. *Perceived Threat from Chinese.* As expected, participants in the COVID-19 condition indicated a significantly higher perceived threat from Chinese people after emergence of the COVID-19 epidemic as compared to the pre-epidemic period ($M_{post\text{-}COVID}$ = 2.07, *SD* = 1.38 vs. $M_{pre\text{-}COVID}$ = 1.90, *SD* = 1.07; $t(100) = 2.15$, $p$ =.03). In contrast, there was no significant difference for participants in the norovirus epidemic condition on the perceived threat from Chinese people after the norovirus epidemic occurred and pre-epidemic period ($M_{post\text{-}norovirus}$ = 1.67, *S.D.* = .99 vs. $M_{pre\text{-}norovirus}$ = 1.67, *S.D.* = .93; $t(100) = 0.21$, $p$ = .84). Moreover, participants in the post-COVID condition indicated a significantly higher perceived threat from Chinese people than those in the post-norovirus condition ($M_{post\text{-}COVID}$ = 2.07, *SD* = 1.38 vs. $M_{post\text{-}norovirus}$ = 1.67, *S.D.* = .99; $t(200) = 2.34$, $p$ = .02).

*Patronage Frequency for Chinese Restaurants.* As expected, participants in the COVID-19 condition indicated significantly lower patronage frequency for Chinese restaurants after the COVID-19 epidemic emerged as compared to the pre-epidemic period ($M_{post\text{-}COVID}$ = 3.68, *SD* = 2.08 vs. $M_{pre\text{-}COVID}$ = 5.53, *SD* = 1.60; $t(100) = 8.19$, $p < .001$). In contrast, there was no significant difference for participants in the norovirus epidemic condition on their patronage frequency for Chinese restaurants after the norovirus epidemic emerged and the pre-epidemic period ($M_{post\text{-}norovirus}$ = 5.18, *SD* = 1.62 vs. $M_{pre\text{-}norovirus}$ = 5.46, *SD* = 1.85; *t*(100) = 1.39, *p* = .17). Moreover, participants in the post-COVID condition indicated a significantly lower patronage frequency for Chinese restaurants as compared to those in the post-norovirus condition ($M_{post\text{-}COVID}$ = 3.68, *SD* = 2.08 vs. $M_{post\text{-}norovirus}$ = 5.18, *SD* = 1.62; *t*(200) = 5.69, *p* < .001).

*Attitude towards Chinese Restaurants.* As expected, there was no significant difference for participants in the COVID-19 epidemic condition on tendency to post negative comments for Chinese restaurants on Yelp after emergence of the COVID-19 epidemic and the pre-epidemic period ($M_{post\text{-}COVID}$ = 2.23, *SD* = 1.52 vs. $M_{pre\text{-}COVID}$ = 2.32, *SD* = 1.38; *t*(100) = .78, *p* =.44). Similarly, there was no significant difference for participants in the norovirus epidemic condition on the tendency to post negative comments for Chinese restaurants on Yelp after the norovirus epidemic emerged and the pre-epidemic period ($M_{post\text{-}norovirus}$ = 2.11, *SD* = 0.51 vs. $M_{pre\text{-}norovirus}$ = 2.18, *SD* = 1.61; *t*(100) = .52, *p* = .61). Moreover, there was no significant difference between participants in the post-COVID conditions and those in the post-virus conditions on tendency to post negative comments for Chinese restaurants on Yelp ($M_{post\text{-}COVID}$ = 2.23, *SD* = 1.52 vs. $M_{post\text{-}norovirus}$ = 2.11, *SD* = 0.51; *t*(200) = .56, *p* = .58).

Study 1 provided direct experimental evidence that the COVID-19 epidemic triggered the U.S. people’s perceived threat from Chinese people. This translated into increased discrimination towards Chinese restaurants, manifesting as reduced patronage frequency for Chinese restaurants instead of increased negative comments.

**A2. Experiment 2: Anti-discrimination towards Chinese Restaurants**

According to the goal pursuit theory (Eccles and Wigfield, 2002; Trope, Liberman, and Wakslak, 2007), individuals' pursuit of goals is influenced by their evaluation of *“desirability”* and *“feasibility”* aspects of available alternatives. Desirability refers to the perceived value or expected outcome of a goal (e.g., which action, writing positive comments or visiting Chinese restaurants, is more effective in supporting Chinese restaurants?). It involves considering the positive and negative consequences associated with pursuing the goal. On the other hand, feasibility pertains to the ease or difficulty of achieving the goal (e.g., how feasible is the action in supporting Chinese restaurants?). Feasibility beliefs are influenced by an individual's capabilities in the specific goal domain and can also be affected by external barriers encountered during goal pursuit (Gollwitzer and Oettingen 2012).

In Experiment 2, we aimed to test the anti-discrimination hypothesis (H2) within an experimental setting, drawing on the goal pursuit theory. Firstly, participants were asked to read an article titled "*Coronavirus' toll on Chinese restaurants is devastating*" and indicate their likelihood of engaging in two supportive actions: "writing positive comments" or "patronizing Chinese restaurants." Subsequently, participants were asked to rate the feasibility and desirability of these two actions in supporting Chinese restaurants. We hypothesized that the prominence of discrimination towards Chinese restaurants following the COVID-19 pandemic would activate participants' anti-discrimination sentiment, primarily manifesting as a preference for "writing positive comments" over "patronizing Chinese restaurants." This inclination is driven by the perception that writing positive comments is both more feasible and desirable in supporting Chinese restaurants.

**Method**. Again, we used MTurk. We only opened this experiment to non-Asian regular customers of Chinese restaurants. A total of 100 participants ($M_{\text{age}}$ = 34.26; 41.0% female) took part in this experiment for a small payment.

First, we asked participants to read a newspaper article titled, "*Coronavirus' toll on Chinese restaurants is devastating*" (adapted Alcorn 2020). Participants summarized the main idea expressed in the article. Then we asked participants "*How likely are you going to write positive comments for Chinese restaurants on yelp as a sign of support for Chinese restaurants?*" and "*How likely are you going to patronize Chinese restaurants as a sign of support for Chinese restaurants?*" (1 = not likely at all 7 = very likely). After that, we asked participants "*Which action (writing positive comments for Chinese restaurants on yelp vs. patronizing Chinese restaurants) is more feasible for you to support Chinese restaurants?*" and indicate the reasons.

**Results**. We found that participants were more likely to post positive comments for Chinese restaurants on Yelp ($M_{comments}$ = 5.82, $SD$ = 1.05) as compared to patronizing Chinese restaurants ($M_{patronize}$ = 5.42, $SD$ = 1.49; $t(99)$ = 2.66, $p$ =.01) as a sign to support Chinese restaurants. Moreover, 85% of the participants indicated that "writing positive comments for Chinese restaurants on Yelp" is more feasible for them to support Chinese restaurants and only 15% of the participants indicated that "patronizing Chinese restaurants" is more feasible. Furthermore, we conducted topic modelling analysis and word frequency analysis on the reasons provided by participants s to reveal the underlying perception of these participants. Regarding feasibility, five topics emerge from the data with the following key words.

Topic 1: ['easy', 'comment', 'write', 'support', 'simple'],

Topic 2: ['idea', 'must', 'far', 'write', 'read'],

Topic 3: ['people', 'visit', 'make', 'thinner', 'transitioning']

Topic 4: ['good', 'idea', 'paragraph', 'main', 'want'],

Topic 5: ['much', 'comment', 'always', 'dish', 'fresh']

Topic 1 directly indicates it is easy to write a supportive review (e.g., "It is simple and free to show support", "Writing positive comments about the restaurant will give the restaurant its positive side again and regain its goodwill", "Easy to write a comment", "good words help more than to visit"). Topics 2 and 3 indicate the geographic distance between participant and Chinese restaurants prevent them from visiting frequently (support our justification for not using patronage as the anti-discrimination measure). Examples include "too far" and "I live far away from Chinese restaurants". Topic 4 is relatively general, while Topic 5 is associated with a specific reason of positive reviews (fresh dishes).

Second, 84% of the participants indicated that "writing positive comments for Chinese restaurants on Yelp" is more effective for them to support Chinese restaurants and only 16% of the participants indicated that "patronizing Chinese restaurants" is more effective for them to support Chinese restaurants. Further topic modelling analysis and word frequency analysis revealed that regarding desirability, five topics emerge from the data with the following key words.

Topic 1: ['influence', 'comment', 'customer', 'people', 'visit'],

Topic 2: ['review', 'way', 'yelp', 'support', 'effective'],

Topic 3: ['idea', 'must', 'effective', 'write', 'main'],

Topic 4: ['comment', 'help', 'positive', 'know', 'time'],

Topic 5: ['good', 'dish', 'fresh', 'huge', 'herb']]

Topic 1 is the most prevalent one where participants state that writing a positive comment is desirable because it can further influence other following customers (e.g., “Writing a comment can influence other customers”, “Social influence among other customers”, and “Positive comments can show our attitude and influence other consumers. Patronizing Chinese restaurant for one time can only order limited food and only bring a little bit increase in their revenue.”). Topics 2, 3, and 4 indicate writing a positive comment is effective and time saving (e.g., “this is more effective and support” and “Writing positive comments for Chinese restaurants on Yelp is an effective way to show support for a Chinese restaurant.”). Topic 5 is associated with a specific reason of positive reviews (fresh dishes).

Study 2 provided direct experimental evidence that the prominence of discrimination towards Chinese restaurants following the COVID-19 pandemic activate participants' anti-discrimination sentiment, primarily manifesting as a preference for "writing positive comments" over "patronizing Chinese restaurants." This inclination is driven by the perception that writing positive comments is both more feasible and desirable in supporting Chinese restaurants.

**B. Identification of non-Chinese customers**

As suggested by ITT, in-groups’ discriminatory attitudes are fostered by their perceived threat from out-groups (Stephan et al. 2002). As noted earlier, moreover, intergroup contact helps reduce in-groups’ discrimination towards out-groups, which may further facilitate anti-discrimination acts (Pettigrew 1998). Based on the theoretical evidence, we focused on discrimination and anti-discrimination behaviors of non-Chinese customers during the pandemic.

Hence, we first differentiated non-Chinese customers from Chinese customers. Specifically, we identified each customer’s race based on his/her name. We employed the most accurate, fine-grained race classifier, *NamePrism* (Ye et al. 2017; Ye and Skiena 2019). Different from traditional name-based race classifiers that use name substrings as features, *NamePrism* exploits homophily patterns in communications (e.g., email, Twitter) to learn name embeddings (Ye et al. 2017). The classifier provided classifications of 39 races, representing 90% of the world’s population. In classifying 13 common races, it yielded an F1 score of 0.795, substantially outperforming other methods (Ye et al. 2017). Notably, its F1 score of classifying “Chinese” names reached the highest value of 0.928, which is particularly valuable for our study. Thus, by leveraging the *NamePrism* classifier, we categorized customers into non-Chinese and Chinese and used only non-Chinese customers in analyses.

**C. Additional Measurement Validation of Racial Discrimination**

One possible concern was whether the number of reviews was a good indicator of a restaurant's performance. Due to privacy-protection and data-release policy differences across states, revenue data were not available for the states we studied. The exception was Vermont, which regularly releases taxable receipts of meals and rooms at the county level on the state's Department of Taxes' website. We examined these data to explore the relationship between revenue and number of reviews on Yelp.com to provide additional justification for our use of the proxy.

We collected monthly taxable receipts of 12 counties[11] from January 2016 to December 2020. The data contained taxable receipts of meal and alcohol sales. Because Vermont was not included in the academic dataset provided by Yelp, we manually searched Yelp.com for the restaurants in each county in Vermont. This resulted in 572 restaurants in 12 counties. We compiled a county-month panel dataset with 717 county-month pairs that had both tax receipts and review-count data. Reported in Panel A of Table A5 are the variables' summary statistics.

Presented in Figure A1 are the monthly taxable receipts and monthly number of reviews, averaged by all counties in each month. The trend of the number of reviews was consistent with that of the taxable receipts. Even during the pandemic, the relationship remained the same.

Then, we estimated the following two models using the data:

$$Taxable\ Receipts_{it} = \beta_0 + \beta_1 Number\ of\ Review_i + \mu_i + \varepsilon_{it} \tag{A1}$$

$$\begin{aligned} Taxable\ Receipts_{it} = {} & \beta_0 + \beta_1 Number\ of\ Review_i + \beta_2 After_t \\ & + \beta_3 Number\ of\ Review_i * After_t + \mu_i + \varepsilon_{it} \end{aligned} \tag{A2}$$

[11] There were 14 counties specified in tax reports in Vermont. However, Essex and Grand Isle counties had missing tax data in roughly 83% and 58% of time periods, respectively. Thus, we removed them from our sample.

where $i$ and $t$ represented county and sequence of time, and $\mu_i$ was the county fixed effect. After reflected a dummy variable indicating whether the date was after the first COVID-19 case was reported in Vermont (March 2020).

Shown in Panel B of Table A5 are the regression results. In Column (1), the findings showed a significantly positive association between the taxable receipts of meals and alcohol and number of reviews on Yelp.com. In Column (2), the results suggested that the outbreak of COVID-19 did not weaken this positive association. All these findings validated our use of the number of reviews on Yelp.com as an apt proxy for restaurant revenue.

**D. A Pilot Study: Spill-Over to Other Asian Restaurants**

We address a potential concern that COVID-19 might have exerted a spill-over effect on other Asian restaurants. This would be plausible, especially when non-Chinese customers would likely have difficulty differentiating Chinese people and those from other Asian countries. To address this issue, we first examined the impact of COVID-19 on East Asian (e.g., Japanese, Korean, and Mongolian) and Southeast Asian (e.g., Singaporean, Vietnamese, and Filipino) restaurants. People from these countries are similar to Chinese people in appearance, and a certain proportion of their cuisine is comparable to Chinese cuisine in taste.

In the estimation, we replaced $Chinese_i$ in specifications (1) and (2) with $Other\_Asian_i$, a dummy variable with a value of "1" indicating that it was an East Asian or a Southeast Asian restaurant, and "0" otherwise. Meanwhile, Chinese restaurants were excluded in the analysis. Presented in Table A4 are the results. During the outbreak phase, there was no difference in both customer patronage frequency and rating premium in ratings of other Asian restaurants ($\beta_2$ = 0.019, $p$ > 0.10 in Model (1); $\beta_2$ = 0.007, $p$ > 0.10 in Model (2); $\beta_2$ = 0.008, $p$ > 0.10 in Model (3)). However, in the recovery phase, Model (1) revealed that customer patronage frequency of other Asian restaurants declined ($\beta_4$ = -0.050, $p$ < 0.05). Nonetheless, Models (2) and (3) showed that customers had increased their rating scores and premium in rating, thus demonstrating more support for these restaurants ($\beta_4$ = 0.048, $p$ < 0.01 in Model (2); $\beta_4$ = 0.033, $p$ < 0.05 in Model (3)).

This set of pilot analyses provided evidence that people from other Asian countries who were similar to Chinese people were also discriminated against due to COVID-19[12]. Despite this, customers still offered some support for them. Therefore, restaurants whose owners were from East Asian or Southeast Asian countries were excluded in subsequent analyses.

**E. General Support and Specific Support for Chinese**

**Manual Labeling**. Considering the low incidence of the explicit support expressed in the review text, we focused on reviews for all restaurants with a 4-star or 5-star rating. The reason for this selection was because a 4-star or 5-star rating indicated a customer's general satisfaction with the restaurant, and thus s/he should be more likely to express general support for the restaurant. There are 398,734 such reviews in our sample; due to the limited labelling capacity, we randomly selected around 3% (11,952 reviews) for manual labeling.

Ten research assistants were hired from a major university in China to label the reviews. They were asked to imagine themselves as an owner of a restaurant in North America, which was experiencing a difficult time during COVID-19. When they read each customer review, they were asked to tell how much explicit support they could perceive from the customer (which was unrelated to positive comments concerning restaurant food, service, or environment). A label of "1" indicated that they perceived a general support for the restaurant, and "0" indicated that there was no evidence of explicit support in the review. Meanwhile, in the cases of "1" labels, the labeler was asked to provide the quote from the review text to support his/her judgement (such as the example provided in Section 7.1). Two labelers assessed each review. If the two labelers disagreed, we employed a third to settle the dispute. For a significant discrepancy in labeling, we invited the same set of three labelers to resolve the disagreement. Through this procedure, among the 11,952 reviews, 6,658 were labeled as "1."

Following a similar approach, to code whether there were expressions of specific support for Chinese people in general in reviews, we focused on reviews for Chinese restaurants with a 4-star or

[12] The lagged effect on discrimination against people from other Asian countries is probably because there were only certain customers paying attention to the COVID-19 outbreak at the beginning. Thus, there was a lower probability of confusing Chinese people with other Asians. After the lockdown, though, all customers became aware of the pandemic, and, among them, conceivably, there was increased likelihood that some might have confused Chinese people with other Asians.

5-star rating. By writing a highly-rated review for Chinese restaurants, the customer was more likely to express his/her specific support for Chinese restaurants/Chinese people in the review text. We manually labelled 7,549 such reviews (approximately 20% of all such reviews).

Six research assistants were hired from a major university in China to label the reviews. They were asked to imagine themselves as an owner of a Chinese restaurant in North America, who was experiencing racial discrimination by having fewer customers compared to other ethnic restaurants during COVID-19. A label of "1" indicated that there was such support specific to Chinese restaurants/Chinese people in the review text, and "0" otherwise. Again, in the cases of "1," the labeler was asked to provide the quote from the review text to support his/her judgement. We used the same approach as above to settle disputes in labeling. Finally, among the 7,549 reviews, 1,929 were labeled as "1."

**Machine Learning**. Before training the classifiers, the review text was pre-processed by removing special characters, unwanted spaces, numbers, and stop words. Words were then converted into lowercase and stemmed to their appropriate roots. Each review was converted into a vector of numeric features. The features were quantified using a term frequency-inverse document frequency (TFIDF) weight. In addition to using the complete review text, we also utilized the quotes that directly demonstrated the explicit support to train the models.

On the basis of the pre-processed vectors of features, a binary classifier was trained using models of a support vector machine, random forests (RFs), Bagging classifier (Bagging), histogram-based gradient boosting classification tree (HGB), and AdaBoost classifier (AdaBoost). To evaluate the performance of different models, we used the traditional evaluation metrics of classification accuracy, F1 score (2×precision×recall/(precision + recall)), and ROC AUC (area under the curve of receiver operating characteristic curve). Presented in Table A7 are the results of a 10-fold cross validation for each model. Based on the metrics, to classify whether there was general support in the remaining reviews, we utilized the best performing model of RFs based on the quotes provided by labelers. To classify whether there was specific support for Chinese people, we employed the best performing model of HGB based on the quotes provided by labelers. The 11,952 reviews were used to train text classification models for classifying whether the review text indicated general support for the restaurant. The 7,549 reviews were used for classifying whether the review text suggested specific support for Chinese.

After applying the text classifier on the remaining reviews, among the total of 361,252 reviews, 17.6% had the indication of general support for the focal restaurant. Among the total of 25,608 reviews of Chinese restaurants, 8.2% had the indication of specific support for Chinese people.

### F. Alternative Models

### F1. Relative Time Model

We also conducted a relative time model with the lead and lag periods as an alternative model specification (Autor, 2003, Burtch et al. 2018). In the relative time model, we included a set of time dummies indicating the chronological distance of an observation period with respect to the timing of the COVID-19 outbreak. This model not only examined the effect of COVID-19 over time (i.e., in both pre- and post-retraction periods), but also validated the parallel trend assumption for the DID analysis (Burtch et al. 2018). The model specification of the relative time model was as follows:

$$\begin{aligned} Y_{it} = \alpha_i + \sum_j \beta_j (Pre\_outbreak_{it}) + \mu Outbreak_{it} + \sum_k \varphi_k (Recovery_{it}) \\ + \sum_j \sigma_j (Chinese_i \times Pre\_outbreak_{it}) + \varsigma Chinese_i \times Outbreak_{it} + \sum_k \tau_k (Chinese_i \times Recovery_{it}) + \varepsilon_{it} \end{aligned} \tag{A3}$$

$$\begin{aligned} Y_{ijt} = \alpha_i + \theta_j + \sum_j \beta_j (Pre\_outbreak_{it}) + \mu Outbreak_{it} + \sum_k \varphi_k (Recovery_{it}) \\ + \sum_j \sigma_j (Chinese_i \times Pre\_outbreak_{it}) + \varsigma Chinese_i \times Outbreak_{it} + \sum_k \tau_k (Chinese_i \times Recovery_{it}) + \varepsilon_{ijt} \end{aligned} \tag{A4}$$

Specifically, *Pre_outbreak* was the vector of relative time dummies of lead periods, including indicator variables for each month before the COVID-19 outbreak (one month was omitted as the baseline); *Outbreak* was the indicator variable for the outbreak period. *Recovery* was the vector of relative time dummies of lag periods, including indicator variables for the months after the reopening time.

Presented in Table A10 are the results of the relative time model. The coefficients for the pre-outbreak dummies were not significant. This suggested that no significant difference in customer patronage and customer feedback between Chinese and non-Chinese restaurants. Therefore, the parallel trend assumption for DID estimation was validated. Moreover, almost all of the coefficients for the recovery dummies were significant, except those for the first month in the recovery phase. One explanation for the non-significant coefficients in the first month since reopening was the capacity restrictions imposed on restaurants at the beginning of the recovery phase. Most states had imposed a capacity restriction on restaurants (e.g., at 50% capacity for restaurants in Georgia at the beginning of reopening) (CBS News, 2020). In this time period, customers who still patronized Chinese restaurants were unlikely to discriminate against Chinese people. When the 50% capacity was reached by non-discrimination customers, there would be no systematic difference in customer patronage frequency between Chinese and non-Chinese restaurants. As a consequence, if customers did not observe that the Chinse restaurant experienced racial discrimination, their anti-discrimination acts would not be evoked. Hence, the effects in the first month of the recovery phase were not significant.

**F2. Zero-Inflated Model**

Although PPML has accounted for many zeros in the number of reviews in a satisfactory level, we still used a zero-inflated model to further address this concern. We modelled whether a customer would visit a restaurant depending on the number of COVID-19 cases reported in the previous week. Based on this, we estimated the zero-inflated model. As shown in Table A11, the results were still held.

**G. Robustness Checks**

We conducted a series of checks to test the robustness of our results. Specifically, in Sections G1 to G8, we teased out alternative explanations of the systematic difference in Chinese and non-Chinese restaurants. In Section G9, we ruled out the possibility of a supply chain shortage for Chinese restaurants.

**G1. Restaurant's Quality**

The inclusion of restaurants' fixed effects did not rule out time-varying confounders within restaurants. Conceivably, COVID-19 might well have altered the actual "quality" of restaurants, which would then have determined customers' rating scores. We conducted the analysis described below to rule out this possibility.

We extracted detailed information regarding the restaurant's quality from a review's textual content. We followed the approach of Shen and Wilkoff (2020) and Li et al. (2021), who computed the "quality score" of each restaurant. First, we chose four pairs of seed words (i.e., "clean and dirty," “delicious and tasteless,” “welcome and unwelcome,” and “comfortable and uncomfortable”) to characterize four dimensions of a restaurant’s quality (i.e., cleanliness, taste, service, and environment). Then we generated two dictionaries of the 10 most similar words and phrases to the seed words by applying *word2vec* (Mikolov et al. 2013) to review texts, which are cleaned, stemmed, and bigramed. Last, we computed the score of each quality’s dimension as the difference between the numbers of positive words (e.g., “clean”) and negative words (e.g., “dirty”) in reviews.

We estimated the main models in Section 5.2 after controlling for the quality measures. If the main results were indeed driven by the quality change of restaurants—rather than racism—the coefficients of interest would become insignificant. However, we found that our main findings continued to hold, as shown in Table A12. This indicated that the main results were not driven, at least not purely, by the different qualities of Chinese and non-Chinese restaurants during COVID-19.

**G2. COVID-19 Precautions**

After the COVID-19 outbreak, restaurants imposed various precautions to contain the spread of COVID-19. For instance, some restaurants required customers and staff to wear masks, and some enforced social-distancing measures. These safety measures could potentially have affected patronage as well as ratings. If so, then the differential changes in Chinese restaurants’ weekly number of reviews and rating scores, compared with their counterparts, might have been consequences of differential precautions taken by restaurants.

To address this concern, we conducted another set of analyses. First, when the number of reviews for each restaurant was not too small, we believed that the precautions taken by each restaurant might have been reflected in the review. Thus, we used the review texts to generate “COVID-19 precaution” variables through the similar approach as detailed in Section G2. We chose “COVID-19 precaution” itself, as well as three commonly mentioned measures (i.e., “mask,” “glove,” and “sanitizer”) as seed words to compute the score of “COVID-19 precaution.” They were used in the analysis to control for the different COVID-19 precautions taken by restaurants. Second, possibly Chinese restaurants might have been more cautious and thus not operated at full scale. To rule out this possibility, we controlled for restaurants’ hours of operation in the analysis.

After controlling for these variables, we found that our main results were qualitatively the same as the baseline model, as shown in Table A12. Therefore, this explanation was ruled out.

**G3. Price Discount**

Another potential reason for the less frequent patronage of Chinese restaurants after the outbreak of COVID-19 might have been the difference in price discounts offered by Chinese and non-Chinese restaurants. If Chinese restaurants offered a smaller price discount to consumers than did non-Chinese restaurants, consumers would likely have tended to visit non-Chinese restaurants more. To rule out this alternative explanation, we used "number of reviews containing words and phrases indicative of price discount," which was generated using the *word2vec* approach—as the dependent variable—and performed the analysis. The results in Table A13 suggested that there was no significant difference between Chinese and non-Chinese restaurants in terms of price promotions before and after the COVID-19 outbreak.

**G4. Restaurant Closures**

Possible concern might exist that the decrease in customer patronage frequency of Chinese restaurants was because Chinese restaurants had been closed more or closed for a longer time during COVID-19 than non-Chinese restaurants. To examine this issue, we employed the dataset from SafeGraph (described in Section 8.1) to determine whether this concern was severe. In general, there were two types of restaurant closure: permanent closure and temporary closure. A permanent closure reflected that the restaurant had chosen to close forever. A temporary closure meant that a restaurant had only shut for a short time period during pandemic and then reopened afterwards.

**G4.1 Permanent closure**

With respect to permanent closures, the SafeGraph data contained a variable indicating if a restaurant closed permanently. Conceivably, if there were more Chinese restaurants closed permanently than non-Chinese restaurants, we should obtain similar results to what we found. In fact, our analysis using SafeGraph data had already taken into consideration the permanent closure. If a restaurant was shut forever, there would be no observation in the data after the closure. In other words, our analysis used the restaurant-week observations only when restaurants were not permanently closed. Therefore, our main finding was unlikely driven by the different number of permanent closures of Chinese and non-Chinese restaurants.

**G4.2 Temporary closure**

Regarding the temporary closures, an alternative explanation of our main finding was that Chinese restaurants chose to close for a longer time than non-Chinese restaurants during the pandemic. Consequently, their business performance should have been worse than non-Chinese restaurants. To understand whether Chinese restaurants (vs. non-Chinese ones) indeed closed for a longer time during the pandemic, we conducted supplementary analyses using the SafeGraph data.

The first step was to determine whether the restaurant had been open during pandemic. We used two definitions of when the restaurants were open and found that the two methods led to nearly identical results. One method defined a restaurant as having remained open when the visit for a given date exceeded zero; and the other method defined a restaurant as having stayed open when its sales for a given date surpassed zero. Then we only included those dates when restaurants were open and excluded the closed dates and re-ran the analysis of Equation (5). We also controlled for restaurant operating hours within each day in the analysis.

Presented in Column (1) and (2) of Table A14 are the estimation results for number of visits and sales utilizing the first definition. Shown in Column (3) and (4) are the findings when the second definition was employed. Both sets of results suggested that our main finding still held. In other words, there was a slim chance that Chinese restaurants' lower frequency of patronage during the pandemic was driven by Chinese restaurants closing for a longer time than non-Chinese restaurants.

**G5. Take-out vs. Dine-in**

Another possible concern was that the decrease in the number of reviews of Chinese restaurants was because a larger proportion of consumers of Chinese restaurants may have chosen take-out options than those of non-Chinese restaurants during the pandemic. Attendant with this idea was possibly that people choosing take-out food were conceivably less likely to write reviews on the platform. To address this concern, we utilized the dataset from SafeGraph (described in Section 8.1).

Following Li, and Wang (2020), the duration of each visit was used to distinguish the takeout and dine-in visits. For the takeout visit, upon arriving at a restaurant, customers typically waited fewer than 20 minutes before their orders were ready for takeout. In addition, takeout visits could be either customers picking up orders themselves or receiving them from delivery drivers via on-demand platform orders. For dine-in visits, we defined visits lasting longer than 20 minutes and shorter than one hour as dine-in visits. Our results were robust to alternative definitions of dine-in visits. As shown in Table A15, both the takeout and dine-in visits of Chinese restaurants decreased more in the recovery period compared with non-Chinese restaurants, and ratio of takeout visits to dine-in visits also did not increase. This finding helped rule out the foregoing alternative explanation.

**G6. Customers' Self-Selection**

Conceivably, the relative higher review ratings of Chinese restaurants during the pandemic may have been driven by customers' self-selection. Specifically, only customers who favored Chinese restaurants might have continued to visit Chinese restaurants after the outbreak of COVID-19; those who had lower perceptions of Chinese restaurants may not have patronized them. Arguably, the possible selection could lead to higher ratings of Chinese restaurants, confounding our main finding. In this section, we tried to test whether after ruling out this self-selection issue, the customers still chose to fight against racial discrimination of Chinese restaurants. In other words, we wanted to know whether customers who continued to visit Chinese restaurants after the outbreak of COVID-19 tended to increase their review ratings of Chinese restaurants, instead of considering the entire customer base. We believe a good comparison is to leverage the within-customer variation of customers who continued to visit Chinese restaurants and compare the same customer's pre-COVID-19 and post-COVID-19 review ratings. Therefore, we conducted the analyses described below.

First, in the Equation 2, we included the customer fixed effects which controlled for the reviewer's time-invariant characteristics. The main results, shown in Table 1 of Section 6, mainly relied on the within-customer variation. They can partially alleviate the abovementioned concern.

Second, we conducted subsample analyses to rule out further the concern on customers' self-selection. As shown in Columns (1) and (9) of Table A16, we undertook subsample analyses on customers who continued to patronize restaurants after the outbreak of COVID-19 and excluded those who did not continue to do so. In Columns (2) and (10), we only used data of customers who patronized restaurants both before and after the outbreak of COVID-19. The results can be interpreted as the change of ratings for the same group of customers before and after the COVID-19 outbreak.

Third, we used the nearest-neighbor matching technique to match each customer leaving a review for a given Chinese restaurant after the outbreak of COVID with a set of closest consumers who left reviews for non-Chinese restaurants. This allowed us to identify two groups of customers that were comparably similar to each. The variables we used for matching included number of visits to Chinese/non-Chinese restaurants before the COVID-19, the ratio of visits of Chinese/non-Chinese restaurants, average rating given to Chinese/non-Chinese restaurants, number of previous reviews given by a customer, whether this customer was an "Elite Reviewer", number of fans s/he had, average stars given by him/her, number of "funny" received, number of "useful" received, and number of "cool" received. Shown in Columns (3) and (11) of Table A16 are the estimation results by using the matched sample. If the main findings on anti-discrimination had been driven by customers' self-selection, the significant results would disappear after we controlled for the change in composition of customers before and after the COVID-19 outbreak. However, as manifested in Table A16, the main results were still held.

Fourth, the selection caused by the racial discrimination resulted in the fact that we were not able to observe what exact ratings customers who stopped patronizing Chinese restaurants would give if they visited Chinese restaurants after the outbreak of COVID-19. One way to alleviate this selection is to find a counterfactual scenario where customers who actually stopped visiting Chinese restaurants would still write reviews for Chinese restaurants after the outbreak of COVID-19. We assume that their preferences would remain consistent without COVID-19[13]. Specifically, we hypothesized that after the outbreak of the pandemic they would visit the exact same Chinese restaurants which they had visited in the same patronage frequency as the pre-COVID-19 period and would give the same ratings

[13] The COVID-19 might cause the actual evaluations of Chinese restaurants given by customers who stopped visiting them after outbreak of COVID-19 become lower because they are ones who are most likely to conduct racial discrimination against Chinese. However, in this paper, our main purpose is to test whether the support of Chinese restaurants given by customers who continued to visit is greater than support of other types of restaurants. Therefore, we do not consider the actual evaluations of Chinese restaurants given by customers who stopped visiting them in the analysis, but include their ratings in normal time (before COVID-19).

which they had given before. Therefore we utilized their evaluations of Chinese restaurants before the outbreak of COVID-19 to simulate their potential evaluations after the outbreak of the pandemic. By using these simulated ratings as well as the actual ratings left by customers, we ran the similar analysis of anti-discrimination in Section 5.2. The analysis results indicate that the findings still hold, as shown in Columns (4) and (12) of Table A16.

Fifth, as main findings in Section 6 indicated that a group of customers had left Chinese restaurants after the outbreak of COVID-19, we tried to construct a similar "selected" control group by mimicking the formation of treatment group which experienced a selection process brought about by the COVID-19. We used the nearest-neighbor matching technique to match each customer who was customer of Chinese restaurants before but never visited them after the outbreak of COVID-19, with a set of closest consumers who were customers of non-Chinese restaurants. In this way, we can find out those customers of non-Chinese restaurants who were more likely to leave non-Chinese restaurants if they experienced the similar selection process as Chinese restaurants. Then we deleted those observations from the control group so that the constructed control group had a similar composition with the treatment group. The variables we used for matching included number of visits to Chinese restaurants before the COVID-19, the ratio of visits to Chinese restaurants, average rating given to Chinese restaurants, average ratings given to non-Chinese restaurants, number of previous reviews given by a customer, whether this customer was an "Elite Reviewer", number of fans s/he had, average stars given by him/her, number of "funny" received, number of "useful" received, and number of "cool" received. As shown in Columns (5) and (13) of Table A16, the main results still held.

In the next analysis, to better leverage the within-customer variation of customers who continued to visit Chinese restaurants, we exclude those customers who stopped patronizing Chinese restaurants after the outbreak of COVID-19 and keep only whose who continued to visit. Furthermore, we compare them (treatment group) with customers who continued to visit other types of restaurants which were not subject to severe pandemic-driven racial discrimination (control group), and conduct a difference-in-difference analysis in order to show that the increase of ratings given by customers of Chinese restaurants (post-COVID-19 ratings minus pre-COVID-19 ratings given by the same group of customers) is larger than increase of ratings given by customers of other types of restaurants. Specially, we choose American food, African and fast food restaurants as control groups. The analysis results indicate that the findings still hold, as shown in Columns (6) , (7), (8) and (14), (15), (16) of Table A16.

Lastly, the experiment in Section 8.2 provided straightforward evidence that customers will increase their ratings after they became cognizant of the salience of discrimination towards Chinese restaurants. This confirmed that our results were indeed driven by customers' supporting behavior, not simply an outcome of customer's self-selection.

**G7. Chain vs Independent Restaurants**

Prior studies (e.g., de Vaan et al. 2021) have shown that, compared to independent restaurants, chain restaurants had more information and resources to respond to the negative shock of COVID-19. Also, there were some different regulations related to delivery orders from these two types of restaurants (Li and Wang 2021). Therefore, we investigated whether there existed some heterogeneity of the effect on chain and independent restaurants. We matched restaurants by their names and identified chain restaurants if two or more restaurants had the exact same name. We treated the number of restaurants that had the same name as the scale of the chain restaurants. As shown in Table A17, there was no significant difference between chain and independent restaurants.

**G8. Competition**

Possibly, the change of number of reviews of non-Chinese restaurants may have been subject to competition with nearby Chinese restaurants. Therefore, we conducted a robustness test by excluding those non-Chinese restaurants that were in proximity to Chinese restaurants (i.e., within 3 km) from our control group. By doing so, we could tease out competition from our analysis. Furthermore, we matched every Chinese restaurant with those geographically distant from non-Chinese restaurants in terms of business attributes. We found that the results were qualitatively the same, as shown in Table A18.

**G9. Supply Chain Shortages**

The deeper drop of patronage frequency of Chinese restaurants could also have resulted from supply chain logistics difficulties associated with delivery of necessary materials and ingredients that may have relied on imports from China. However, in the months after the COVID-19 outbreak, though travel between China and the U.S. was greatly impacted, trade was not. According to data released by the U.S. Census Bureau[14] in Table A19, both the imports and exports from/to China increased significantly after the COVID-19 outbreak, partly alleviating this concern. Further, if lower patronage frequency of Chinese restaurants was mainly caused by a shortage of requisite materials, other types of restaurants—such as Latin American—should also have been similarly influenced. The estimation results in Section I1, however, suggested that this was not the case. Therefore, we rule out the possibility that supply chain shortages were the main reason behind this issue.

**H. Sensitivity Analysis**

To investigate the sensitivity of our results to definitions of outbreak and recovery periods, we re-ran the analyses using alternative definitions of outbreak and recovery periods. First, we defined the pre-outbreak period as being from November 2019 to January 2020 (on January 30th, the WHO declared the 2019-nCov as PHEIC), the outbreak phase was from February 2020 to April 2020, and the recovery phase was from May 2020 to December 2020. Second, we defined the pre-outbreak period was from November 2019 to January 2020, the outbreak phase was from February 2020 to the reopening day, and the recovery phase was from the reopening day to December 2020. Third, we defined the pre-outbreak period was from November 2019 to the day when the first COVID-19 case was reported in a state, the outbreak phase was from the day when the first COVID-19 case was reported to the reopening day, and the recovery phase was from the reopening day to December 2020. As shown in Table A20, all these results showed that our main findings were robust to alternative definitions of the outbreak and recovery periods.

**I. Falsification Tests**

**I1. Test for Other Ethnic Restaurants**

We also tested whether the results held for other ethnic restaurants. If the difference in patronage frequency and ratings between Chinese and non-Chinese restaurants were due to racial and anti-racial discrimination targeted against Chinese, we would not likely have seen the similar pattern for other

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[14] See https://www.census.gov/foreign-trade/balance/c5700.html.

ethnic restaurants. We performed the same analyses for Latino and non-Latino restaurants. We did not find a significant difference in terms of patronage frequency or ratings, as displayed in Columns (1) to (3) of Table A21.

**I2. Placebo Test**

To validate that our findings indeed resulted from the COVID-19 outbreak, we re-estimated our model using a new date of "COVID-19 outbreak" as a placebo test, following the spirit of Finkelstein (2002). We expected that all coefficients of interest would be attenuated toward zero because the new treatment date was purely random. As the impact of COVID-19 could be long-term, it was not appropriate to choose a date after the COVID-19 outbreak. Therefore, we chose the same time in the previous year as the new date of the "COVID-19 outbreak." As shown in Table A22, none of the coefficients of interest was statistically significant, indicating that the main findings were driven by the COVID-19 outbreak, not by some random event.

**J. Construction of Variable "*Premium_in_rating*"**

We leveraged the tool of VADER (for Valence Aware Dictionary for sEntiment Reasoning), which is a parsimonious rule-based model, to assess sentiment (Hutto and Gilbert 2014). It is available in the Natural Language Toolkit (NLTK) package in Python. The VADER tool is widely used and found to outperform the mainstream sentiment analysis tools, and even human raters, in assessing the sentiment of user-generated content (Hutto and Gilbert 2014). We used the "compound" score provided by VADER, which a single summary measure of the sentiment of a text based on its individual words' sentiment scores.

In VADER, each word in the lexicon is rated as positive, negative, or neutral, and is assigned a score between -4 (extremely negative) and +4 (extremely positive). It also takes into account factors such as punctuation, capitalization, degree modifiers, shift in polarity due to conjunctions, etc. The compound score for a sentence or a text is then calculated by summing up all the scores of the words present in the text and normalizing it to be between -1 (most extreme negative) and +1 (most extreme positive). To compute "*premium_in_rating*", we rescale the compound score to the same range of rating (i.e., from 1 to 5), and subtract it from the rating. The examples of mappings for *premium_in_rating*, *rating*, *compound score*, and the corresponding *review text* are available in Table A24. The statistics of all the relevant variables are presented in Table A2.

**K. Review Bombing**

In the food service context, people who had prejudice towards Chinese restaurants might deliberately write negative reviews or reviews which contain racism words for Chinese restaurants, i.e., review bombing. In this section, we attempted to see whether there existed evidence for it.

Firstly, we tested whether users deliberately gave low ratings to Chinese restaurants. If some users tried to hurt Chinese restaurants by leaving negative review, we would observe the increase of the proportion of low-rating reviews such as one-star rating. As shown in Column (1) of Table A23, the proportion of 1-star reviews given to Chinese restaurants decreased compared with non-Chinese restaurants, suggesting no evidence of more deliberate negative reviews given by users. And Column (2) shows that the proportion of 5-star reviews of Chinese restaurants increased. Then we categorized all reviews into low-rating reviews (lower than or equal to 3 stars) and high-rating reviews (higher than or equal to 4 stars). And we found that Chinese restaurants' proportion of low-rating reviews decreased and proportion of high-rating reviews increased, as shown in Column (3) and (4) of Table A23. Column (5) presented that the variance of ratings did not change significantly.

Secondly, we used textual analysis to look for racist words in the review text in yelp by taking the following steps:

In Step 1, we searched for dictionaries which contain words expressing racism. We found 4 majors dictionaries and combine them to construct a comprehensive one. The 4 dictionaries are:

http://rsdb.org/races; https://relatedwords.io/racial-discrimination;

https://en.wikipedia.org/wiki/List_of_ethnic_slurs;

https://en.wikipedia.org/wiki/List_of_ethnic_slurs_and_epithets_by_ethnicity

In Step 2, we matched yelp's review text with the dictionary constructed in step 1, and found those potentially racist reviews.

In Step 3, we conducted sentiment analyses for those potentially racist reviews spotted in step 2 by two different approaches: LIWC (Kovacs and Kleinbaum, 2019), and NLTK (Micu et al. 2017).

In Step 4, we identified those reviews of which the sentiment scores generated by two approaches are both negative, and treated them as the final review list, because they contain potentially racist words as well as negative sentiment.

However, in the final review list, we are not able to find the truly racist reviews, because in most reviews the reviewers are complaining about the food or staff, and happen to use those potentially racism words in the reviews to exaggerate their feelings, but they are not purposefully racially discriminating against some group of people.

To sum up, in this context we did not find evidence for users deliberating giving low ratings or leaving racist review due to racial discrimination. The most likely reason is that the algorithm of Yelp[15] is able to find and delete most of fake reviews, i.e., reviews which are written by people who do not actually patronize the corresponding restaurant, and racist reviews, i.e., reviews which express racism purposefully and strongly. And it is unlikely for a person to patronize a Chinese restaurant in person during the pandemic if his/her main purpose is to write a negative review of it.

## L. Alternative Packages to Conduct Sentiment Analyses

We also run robustness tests by employing two commonly used alternative packages (TextBlob and AFINN) to conduct sentiment analyses and then generating the measure of rating premium. As shown by Table A25, the results are consistent with the main findings.

[15] https://www.yelp.com/guidelines. Accessed on June 23, 2023

**Table A1. Racial Discrimination Studies in Consumer Markets**

| Victim / Perpetrator | Individual | Business |
|---|---|---|
| **Business** | **Offline**<br>***Retail:*** Salespersons discriminated against Black customers (Schreer et al. 2009)<br>***Housing***: 1. Landlords discriminated against black-white audits (Ondrich et al. 1999); 2. Agents discriminate black customers (Yinger 1986)<br>***Car sales:*** Car dealers discriminated against black customers (Ayres 1995; Ayres and Siegelman 1995)<br>***Healthcare***: Clinicians/Physicians discriminated against black patients (Blair et al. 2013, Penner et al. 2010)<br><br>**Online**<br>***Airlines***: African American customers were less likely to receive responses to their complaints in corporate social media (Gunarathne et al. 2022) | |
| **Individual** | **Online**<br>***Airbnb.com***: 1. Black hosts charged less than white hosts (Edelman and Luca 2014); 2. Guests with black names had lower acceptance rates than guests with white names (Edelman et al. 2017)<br>***Craigslist***: 1. Black sellers received fewer offers than white sellers (Doleac and Stein 2013); 2. Arab woman customers received fewer replies than white counterparts (Ghoshal and Gaddis 2015)<br>***eBay.com***: Price of an item held in a dark-skinned hand was less than that held in a light-skinned hand (Ayres et al. 2015)<br>***Prosper.com***: Black fundraisers are less likely to receive fund than white fundraisers (Pope and Sydnor 2011)<br>***Kickstarter.com***: African American fundraisers are less likely to receive fund than white fundraisers (Younkin and Kuppuswamy 2018)<br>***Uber and Lyft***: Drivers with African American sounding names had a double cancel rate than white drivers (Ge et al. 2020) | Current study Huang et al. (2023) |

**Table A2. Summary Statistics**

| Variable | Obs. | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| **Panel A: business level** | | | | | |
| Chinese | 35,194 | 0.073 | 0.261 | 0 | 1 |
| Wifi | 35,194 | 0.476 | 0.499 | 0 | 1 |
| Takeout | 35,194 | 0.911 | 0.285 | 0 | 1 |
| Good For Groups | 35,194 | 0.687 | 0.464 | 0 | 1 |
| Outdoor Seating | 35,194 | 0.461 | 0.499 | 0 | 1 |
| Good For Kids | 35,194 | 0.688 | 0.463 | 0 | 1 |
| Delivery | 35,194 | 0.647 | 0.478 | 0 | 1 |
| Reservations | 35,194 | 0.280 | 0.449 | 0 | 1 |
| Credit Cards | 35,194 | 0.793 | 0.405 | 0 | 1 |
| Has TV | 35,194 | 0.644 | 0.479 | 0 | 1 |
| Business Parking | 35,194 | 0.729 | 0.444 | 0 | 1 |
| Ambience | 35,194 | 0.586 | 0.493 | 0 | 1 |
| Good For Meal | 35,194 | 0.529 | 0.499 | 0 | 1 |
| Alcohol | 35,194 | 0.425 | 0.494 | 0 | 1 |
| Bike Parking | 35,194 | 0.614 | 0.487 | 0 | 1 |
| Caters | 35,194 | 0.416 | 0.493 | 0 | 1 |
| Appointment Only | 35,194 | 0.004 | 0.062 | 0 | 1 |
| Happy Hour | 35,194 | 0.188 | 0.391 | 0 | 1 |
| Music | 35,194 | 0.037 | 0.190 | 0 | 1 |
| Noise Level | 35,194 | 0.593 | 0.491 | 0 | 1 |
| Wheelchair Accessible | 35,194 | 0.307 | 0.461 | 0 | 1 |
| Dogs Allowed | 35,194 | 0.075 | 0.263 | 0 | 1 |
| **Panel B: user level** | | | | | |
| Review Count | 469,614 | 29.839 | 104.311 | 0 | 14,691 |
| User Useful Count | 469,614 | 54.743 | 786.471 | 0 | 182,600 |
| User Funny Count | 469,614 | 21.999 | 501.220 | 0 | 166,330 |
| User Cool Count | 469,614 | 33.114 | 691.942 | 0 | 175,463 |
| Average Stars | 469,614 | 3.688 | 1.092 | 1 | 5 |
| Is_Chinese | 469,585 | 0.042 | 0.200 | 0 | 1 |
| Fans Count | 469,614 | 1.954 | 21.129 | 0 | 3,511 |
| Compliment: Hot | 469,614 | 1.867 | 67.379 | 0 | 20,249 |
| Compliment: More | 469,614 | 0.310 | 10.456 | 0 | 4,275 |
| Compliment: Profile | 469,614 | 0.196 | 15.469 | 0 | 6,924 |
| Compliment: Cute | 469,614 | 0.101 | 6.294 | 0 | 2,962 |
| Compliment: List | 469,614 | 0.058 | 5.829 | 0 | 2,555 |
| Compliment: Note | 469,614 | 1.642 | 36.898 | 0 | 13,248 |
| Compliment: Plain | 469,614 | 3.907 | 166.383 | 0 | 90,858 |
| Compliment: Cool | 469,614 | 3.313 | 106.392 | 0 | 46,858 |
| Compliment: Funny | 469,614 | 3.313 | 106.392 | 0 | 46,858 |
| Compliment: Writer | 469,614 | 1.280 | 35.945 | 0 | 15,225 |
| Compliment: Photos | 469,614 | 1.570 | 95.112 | 0 | 53,854 |
| **Panel C: review level** | | | | | |
| Rating | 1,041,586 | 3.824 | 1.461 | 1 | 5 |
| Useful Count | 1,041,586 | 0.785 | 3.177 | 0 | 446 |
| Funny Count | 1,041,586 | 0.249 | 1.782 | 0 | 264 |
| Cool Count | 1,041,586 | 0.467 | 2.796 | 0 | 371 |
| compound | 1,041,586 | 0.648 | 0.550 | -1 | 1 |
| compound_rescaled | 1,041,586 | 4.296 | 1.100 | 1 | 5 |
| premium_in_rating | 1,041,586 | -0.472 | 1.086 | -3.999 | 3.982 |

**Table A3. Dates of first COVID-19 case, stay-at-home order, and reopening**

| State | 1st case date | Stay-at-home order date | Reopening date |
|---|---|---|---|
| British Columbia | 05 March 2020 | 16 March 2020 | 19 May 2020 |
| Colorado | 04 March 2020 | 24 March 2020 | 25 May 2020 |
| Florida | 01 March 2020 | 01 April 2020 | 04 May 2020 |
| Georgia | 02 March 2020 | 23 March 2020 | 27 April 2020 |
| Massachusetts | 01 February 2020 | 23 March 2020 | 18 May 2020 |
| Ohio | 09 March 2020 | 22 March 2020 | 21 May 2020 |
| Oregon | 01 March 2020 | 16 March 2020 | 15 May 2020 |
| Texas | 12 February 2020 | 19 March 2020 | 08 May 2020 |
| Washington | 21 January 2020 | 23 March 2020 | 06 May 2020 |

**Table A4. Spill-Over Effect on Other Asian Restaurants**

| | (1)<br>Patronage | (2)<br>Rating | (3)<br>Premium in Rating |
|---|---|---|---|
| *Outbreak* | 0.017 | -0.013 | 0.003 |
| | (0.012) | (0.018) | (0.016) |
| ***Other_Asian* × *Outbreak*** | **0.019** | **0.007** | **0.008** |
| | **(0.023)** | **(0.022)** | **(0.020)** |
| *Recovery* | -0.522** | 0.055** | 0.084** |
| | (0.011) | (0.014) | (0.012) |
| ***Other_Asian* × *Recovery*** | **-0.050*** | **0.048**** | **0.033*** |
| | **(0.023)** | **(0.015)** | **(0.014)** |
| *Constant* | -0.387** | 3.950** | -0.492** |
| | (0.005) | (0.006) | (0.006) |
| Monthly FE | √ | √ | √ |
| Restaurant FE | √ | √ | √ |
| Customer FE | | √ | √ |
| Observations | 1,465,110 | 236,594 | 236,594 |
| No. of restaurants | 28,739 | 21,820 | 21,820 |
| No. of customers | | 59,267 | 59,267 |
| $R^2$ | 0.264 | 0.603 | 0.490 |

*Notes*: Robust standard errors are in parentheses; ** p<0.01, * p<0.05, † p<0.10.
Chinese restaurants have been excluded in the analysis.

**Table A5. Number of Reviews and Restaurant Revenue**

| **Panel A Summary Statistics** | | | | | |
|---|---|---|---|---|---|
| **Variable** | **Obs** | **Mean** | **SD** | **Min** | **Max** |
| Taxable receipts (million dollars) | 717 | 8.434 | 8.404 | 1.122 | 45.165 |
| Number of reviews | 717 | 9.556 | 8.677 | 0 | 44 |

| **Panel B FE regression** | | |
|---|---|---|
| | (1)<br>Meals & alcohol taxable receipts | (2)<br>Meals & alcohol taxable receipts |
| *Number of reviews* | 0.129** | 0.076* |
| | (0.017) | (0.033) |
| *After* | | -3.456† |
| | | (1.655) |
| *Number of reviews × After* | | 0.127 |
| | | (0.110) |
| *Constant* | 7.198** | 8.139** |
| | (0.161) | (0.453) |
| County FE | √ | √ |
| Observations | 717 | 717 |
| $R^2$ | 0.928 | 0.942 |

*Notes*: Robust standard errors are in parentheses; ** p<0.01, * p<0.05, † p<0.10.
*After* is a dummy variable indicating whether the date was after the first COVID-19 case was reported in Vermont (March 2020).

**Table A6. Results Estimated with Control Variables**

| | (1)<br>Patronage | (2)<br>Rating | (3)<br>Premium in Rating |
|---|---|---|---|
| *Chinese* | 0.131** | -0.005 | -0.012 |
| | (0.036) | (0.013) | (0.011) |
| *Outbreak* | 0.052** | -0.001 | 0.009 |
| | (0.016) | (0.011) | (0.010) |
| ***Chinese* × *Outbreak*** | **-0.147**** | **0.041** | **0.027** |
| | **(0.036)** | **(0.026)** | **(0.024)** |
| *Recovery* | -0.565** | 0.054** | 0.074** |
| | (0.011) | (0.008) | (0.007) |
| ***Chinese* × *Recovery*** | **-0.066*** | **0.057**** | **0.038*** |
| | **(0.029)** | **(0.018)** | **(0.015)** |
| *Restaurant-related control variables* | | | |
| stars | 0.445** | 0.635** | 0.267** |
| | (0.015) | (0.004) | (0.004) |
| Wifi | -0.034† | -0.017** | -0.030** |
| | (0.020) | (0.006) | (0.005) |
| Takeout allowed | 0.049 | 0.040** | 0.030** |
| | (0.035) | (0.011) | (0.010) |
| Good for groups | -0.151** | 0.001 | 0.009 |
| | (0.023) | (0.007) | (0.007) |
| Outdoor setting | 0.338** | -0.034** | -0.041** |
| | (0.019) | (0.006) | (0.005) |
| Good for kids | -0.026 | 0.002 | 0.031** |
| | (0.025) | (0.007) | (0.006) |
| Restaurants delivery | 0.525** | -0.029** | 0.012* |
| | (0.021) | (0.006) | (0.005) |
| Restaurants reservations | -0.013 | 0.022** | -0.030** |
| | (0.022) | (0.006) | (0.005) |
| Business accepts credit cards | 0.389** | -0.052** | 0.029** |
| | (0.027) | (0.008) | (0.009) |
| Has TV | -0.117** | 0.015** | 0.012* |
| | (0.021) | (0.006) | (0.005) |
| Business parking | 0.188** | 0.026** | 0.003 |
| | (0.024) | (0.008) | (0.007) |
| Ambience | 0.369** | -0.002 | -0.032** |
| | (0.024) | (0.008) | (0.007) |
| Good for meal | 0.249** | 0.008 | 0.003 |
| | (0.022) | (0.008) | (0.007) |
| Alcohol | 0.242** | 0.012† | -0.038** |
| | (0.024) | (0.007) | (0.006) |
| Bike parking | -0.290** | 0.000 | 0.012* |
| | (0.020) | (0.006) | (0.005) |
| Caters | -0.014 | -0.004 | 0.003 |
| | (0.019) | (0.006) | (0.005) |
| By appointment only | 0.412** | 0.009 | 0.019 |
| | (0.126) | (0.027) | (0.023) |
| Happy hour | 0.162** | -0.024** | -0.035** |
| | (0.024) | (0.007) | (0.006) |
| Music | -0.126** | 0.010 | -0.006 |
| | (0.047) | (0.013) | (0.011) |
| Noise level | 0.237** | -0.007 | -0.001 |
| | (0.023) | (0.007) | (0.006) |
| Wheelchair accessible | 0.253** | 0.007 | -0.013* |
| | (0.020) | (0.006) | (0.005) |
| Dogs allowed | 0.170** | -0.012 | -0.003 |
| | (0.032) | (0.008) | (0.007) |

| | | | |
|---|---|---|---|
| Price | 0.315** | 0.027** | -0.036** |
| | (0.017) | (0.006) | (0.005) |
| No. of rival restaurant (in 3 km) | 0.079** | -0.008 | -0.005 |
| | (0.022) | (0.006) | (0.006) |
| *Customer-related control variables* | | | |
| No. of reviews | | 0.061** | -0.173** |
| | | (0.011) | (0.050) |
| No. of fans | | -0.099** | 0.021 |
| | | (0.027) | (0.097) |
| Average stars given | | 0.869** | 0.378** |
| | | (0.003) | (0.003) |
| Compliment by others | | 0.017† | 0.010 |
| | | (0.010) | (0.016) |
| Constant | -4.967** | -1.955** | -2.860** |
| | (0.084) | (0.022) | (0.022) |
| Monthly FE | √ | √ | √ |
| Observations | 1,578,912 | 346,759 | 346,759 |
| No. of restaurants | 30,956 | 27,210 | 27,210 |
| No. of customers | | 190,502 | 190,502 |
| $R^2$ | 0.128 | 0.458 | 0.158 |

*Notes*: Robust standard errors are in parentheses; ** $p<0.01$, * $p<0.05$, † $p<0.10$.
Regarding customer-related control variables, "Compliment by others" was computed as the average of "Compliment hot, Compliment more, Compliment profile, Compliment cute, Compliment list, Compliment note, Compliment plain, Compliment cool, Compliment writer, and Compliment photos." "No. of reviews" and "No. of fans" were measured in thousands.

### Table A7. 10-Fold Cross Validation Results of Text Classifiers

| | SVM | RFs | Bagging | HGB | AdaBoost |
|---|---|---|---|---|---|
| **Complete text for general support** | | | | | |
| Accuracy | 0.603 | **0.616** | 0.609 | 0.610 | 0.593 |
| F1 | 0.672 | **0.708** | 0.676 | 0.681 | 0.651 |
| ROC AUC | 0.632 | **0.647** | 0.637 | 0.644 | 0.615 |
| **Quotes for general support** | | | | | |
| Accuracy | 0.921 | **0.927** | 0.910 | 0.926 | 0.911 |
| F1 | 0.930 | **0.936** | 0.920 | 0.934 | 0.921 |
| ROC AUC | 0.977 | **0.981** | 0.970 | 0.980 | 0.970 |
| **Complete text for Chinese support** | | | | | |
| Accuracy | **0.751** | 0.746 | 0.753 | 0.740 | 0.744 |
| F1 | 0.160 | 0.054 | 0.337 | 0.332 | **0.366** |
| ROC AUC | 0.705 | **0.721** | 0.699 | 0.689 | 0.671 |
| **Quotes for Chinese support** | | | | | |
| Accuracy | 0.852 | 0.851 | 0.845 | **0.853** | 0.831 |
| F1 | 0.646 | 0.649 | 0.653 | **0.689** | 0.642 |
| ROC AUC | 0.883 | 0.897 | 0.876 | **0.905** | 0.888 |

**Table A8. Heterogeneity of Local Racial Tension**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Patronage | Rating | Premium in Rating | Patronage | Rating | Premium in Rating |
| | z is % of Chinese people | | | z is incidence of anti-Asian crimes | | |
| *Outbreak* | 0.021 | -0.004 | 0.001 | -0.163** | -0.007 | -0.002 |
| | (0.013) | (0.028) | (0.026) | (0.017) | (0.024) | (0.022) |
| *Chinese × Outbreak* | -0.074† | 0.002 | 0.065 | -0.060 | -0.076 | -0.025 |
| | (0.044) | (0.072) | (0.065) | (0.051) | (0.054) | (0.047) |
| *Outbreak × z* | -0.014† | 0.010 | 0.014 | 0.024** | -0.001 | -0.000 |
| | (0.008) | (0.018) | (0.017) | (0.009) | (0.002) | (0.002) |
| ***Chinese × Outbreak × z*** | **-0.054*** | **-0.009** | **-0.063** | **-0.043** | **0.009** | **0.002** |
| | **(0.027)** | **(0.047)** | **(0.042)** | **(0.031)** | **(0.006)** | **(0.005)** |
| *Recovery* | -0.488** | -0.005 | 0.051** | -0.420** | 0.050** | 0.088** |
| | (0.012) | (0.020) | (0.018) | (0.013) | (0.017) | (0.015) |
| *Chinese × Recovery* | 0.040 | 0.142** | 0.138** | 0.061 | 0.054 | 0.083** |
| | (0.036) | (0.047) | (0.040) | (0.041) | (0.033) | (0.028) |
| *Recovery × z* | -0.070** | 0.060** | 0.033** | -0.110** | 0.004* | 0.002† |
| | (0.007) | (0.013) | (0.011) | (0.010) | (0.001) | (0.001) |
| ***Chinese × Recovery × z*** | **-0.084**** | **-0.070**** | **-0.050*** | **-0.066†** | **0.006** | **0.001** |
| | **(0.020)** | **(0.026)** | **(0.023)** | **(0.037)** | **(0.004)** | **(0.004)** |
| *Constant* | -0.430** | 3.912** | -0.509** | -0.582** | 3.932** | -0.499** |
| | (0.005) | (0.007) | (0.006) | (0.012) | (0.008) | (0.007) |
| Monthly FE | √ | √ | √ | √ | √ | √ |
| Restaurant FE | √ | √ | √ | √ | √ | √ |
| Customer FE | | √ | √ | | √ | √ |
| Observations | 1,389,372 | 204,489 | 204,489 | 1,105,887 | 178,219 | 178,219 |
| No. of restaurants | 27,212 | 20,148 | 20,148 | 21,936 | 16,703 | 16,703 |
| No. of customers | | 52,960 | 52,960 | | 47,287 | 47,287 |
| $R^2$ | 0.263 | 0.617 | 0.500 | 0.261 | 0.617 | 0.498 |

Notes: Robust standard errors in parentheses; ** p<0.01, * p<0.05, † p<0.10.

**Table A9. Change in rating based on repeat customers**

| | (1) | (2) |
|---|---|---|
| | Rating | Premium in Rating |
| *Outbreak* | 0.004 | 0.015 |
| | (0.019) | (0.017) |
| *Chinese* × *Outbreak* | -0.029 | -0.049 |
| | (0.039) | (0.035) |
| *Chinese* × *Repeat_customer* | -0.235* | -0.141 |
| | (0.116) | (0.100) |
| *Outbreak* × *Repeat_customer* | -0.156 | -0.115 |
| | (0.242) | (0.223) |
| ***Chinese* × *Outbreak* ×** | **0.324** | **0.386** |
| ***Repeat_customer*** | **(0.261)** | **(0.240)** |
| *Recovery* | 0.063** | 0.089** |
| | (0.014) | (0.013) |
| *Chinese* × *Recovery* | 0.044 | 0.065** |
| | (0.027) | (0.023) |
| *Recovery* × *Repeat_customer* | -0.171 | -0.119 |
| | (0.125) | (0.110) |
| ***Chinese* × *Recovery* ×** | **0.366*** | **0.253†** |
| ***Repeat_customer*** | **(0.161)** | **(0.133)** |
| *Constant* | 3.913** | -0.508** |
| | (0.007) | (0.006) |
| Monthly FE | √ | √ |
| Restaurant FE | √ | √ |
| Customer FE | √ | √ |
| Observations | 204,489 | 204,489 |
| No. of restaurants | 20,148 | 20,148 |
| No. of customers | 52,960 | 52,960 |
| R2 | 0.617 | 0.500 |

*Notes*: Robust standard errors are in parentheses; ** p<0.01, * p<0.05, † p<0.10.

**Table A10. Results of relative time model**

| | (1) | (2) | (3) |
|---|---|---|---|
| | Patronage | Rating | Premium in Rating |
| Pre-outbreak (t = -4) | -0.004 | -0.034* | -0.004 |
| | (0.009) | (0.015) | (0.012) |
| **Chinese × Pre-outbreak (t = -4)** | **-0.042** | **0.055** | **-0.012** |
| | **(0.029)** | **(0.048)** | **(0.033)** |
| Pre-outbreak (t = -3) | -0.063** | -0.032* | 0.010 |
| | (0.010) | (0.015) | (0.013) |
| **Chinese × Pre-outbreak (t = -3)** | **0.023** | **0.072** | **0.019** |
| | **(0.040)** | **(0.048)** | **(0.023)** |
| Pre-outbreak (t = -2) | 0.003 | -0.038** | -0.015 |
| | (0.009) | (0.015) | (0.014) |
| **Chinese × Pre-outbreak (t = -2)** | **-0.050** | **0.075** | **0.022** |
| | **(0.031)** | **(0.047)** | **(0.026)** |
| Outbreak | -0.247** | -0.006 | 0.011 |
| | (0.010) | (0.015) | (0.017) |
| **Chinese × Outbreak** | **-0.144**** | **0.040** | **-0.013** |
| | **(0.039)** | **(0.048)** | **(0.027)** |
| Recovery (t = 1) | -0.827** | 0.045* | 0.092** |
| | (0.014) | (0.018) | (0.021) |
| Chinese × Recovery (t = 1) | 0.035 | 0.047 | 0.077 |
| | (0.046) | (0.058) | (0.065) |
| Recovery (t = 2) | -0.542** | 0.040* | 0.066** |
| | (0.013) | (0.020) | (0.016) |
| Chinese × Recovery (t = 2) | -0.085† | 0.112† | 0.064† |
| | (0.045) | (0.064) | (0.035) |
| Recovery (t = 3) | -0.437** | 0.001 | 0.071** |
| | (0.013) | (0.018) | (0.016) |
| Chinese × Recovery (t = 3) | -0.104* | 0.190** | 0.114** |
| | (0.043) | (0.057) | (0.026) |
| Recovery (t = 4) | -0.390** | 0.033* | 0.087** |
| | (0.013) | (0.017) | (0.012) |
| Chinese × Recovery (t = 4) | -0.134** | 0.093† | 0.072† |
| | (0.045) | (0.053) | (0.039) |
| Recovery (t = 5) | -0.387** | -0.014 | 0.060** |
| | (0.013) | (0.017) | (0.014) |
| Chinese × Recovery (t = 5) | -0.185** | 0.118* | 0.066† |
| | (0.043) | (0.053) | (0.035) |
| Recovery (t >= 6) | -0.522** | 0.022 | 0.081** |
| | (0.012) | (0.016) | (0.015) |
| Chinese × Recovery (t >= 6) | -0.078* | 0.105* | 0.096* |
| | (0.040) | (0.048) | (0.034) |
| Constant | -0.410** | 3.940** | -0.502** |
| | (0.007) | (0.010) | (0.009) |
| Restaurant FE | √ | √ | √ |
| Customer FE | | √ | √ |
| Observations | 1,389,372 | 204,489 | 204,489 |
| No. of restaurants | 27,212 | 20,148 | 20,148 |
| No. of customers | | 52,960 | 52,960 |
| $R^2$ | 0.261 | 0.617 | 0.500 |

*Notes*: Robust standard errors in parentheses; ** p<0.01, * p<0.05, † p<0.10.

**Table A11. Results of zero-inflated model**

| | (1)<br>Patronage |
|---|---|
| *Chinese* | 0.104** |
| | (0.013) |
| *Outbreak* | 0.039** |
| | (0.014) |
| ***Chinese × Outbreak*** | **-0.125**** |
| | **(0.031)** |
| *Recovery* | -0.581** |
| | (0.009) |
| ***Chinese × Recovery*** | **-0.062**** |
| | **(0.018)** |
| *Constant* | -3.999** |
| | (0.025) |
| ***Inflated*** | |
| *No. of new COVID cases* | -0.006** |
| | (0.000) |
| *Constant* | 0.094** |
| | (0.007) |
| Monthly FE | √ |
| Control variables | √ |
| Observations | 1,578,912 |
| No. of restaurants | 30,956 |
| $R^2$ | 0.142 |

*Notes*: Robust standard errors in parentheses; ** p<0.01, * p<0.05, † p<0.10.
No. of new COVID cases is measured in thousands.

**Table A12. Rule out Alternative Explanations: Quality and COVID-19 Precautions**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Patronage | Patronage | Rating | Rating | Premium in Rating | Premium in Rating |
| *Outbreak* | 0.021† | 0.021† | 0.007 | 0.009 | 0.016 | 0.017 |
| | (0.012) | (0.012) | (0.018) | (0.018) | (0.017) | (0.017) |
| ***Chinese* × *Outbreak*** | **-0.136**** | **-0.136**** | **-0.019** | **-0.017** | **-0.023** | **-0.022** |
| | **(0.033)** | **(0.033)** | **(0.036)** | **(0.036)** | **(0.034)** | **(0.034)** |
| *Recovery* | -0.534** | -0.548** | 0.062** | 0.082** | 0.086** | 0.099** |
| | (0.011) | (0.011) | (0.014) | (0.014) | (0.012) | (0.013) |
| ***Chinese* × *Recovery*** | **-0.068*** | **-0.062*** | **0.060*** | **0.057*** | **0.075**** | **0.073**** |
| | **(0.029)** | **(0.029)** | **(0.024)** | **(0.024)** | **(0.022)** | **(0.022)** |
| *Constant* | -0.427** | -0.433** | 3.653** | 3.653** | -0.594** | -0.594** |
| | (0.006) | (0.006) | (0.007) | (0.007) | (0.006) | (0.006) |
| Quality | √ | √ | √ | √ | √ | √ |
| Covid Precaution | | √ | | √ | | √ |
| Monthly FE | √ | √ | √ | √ | √ | √ |
| Restaurant FE | √ | √ | √ | √ | √ | √ |
| Customer FE | | | √ | √ | √ | √ |
| Observations | 1,389,372 | 1,389,372 | 204,489 | 204,489 | 204,489 | 204,489 |
| No. of restaurants | 27,212 | 27,212 | 20,148 | 20,148 | 20,148 | 20,148 |
| No. of customers | | | 52,960 | 52,960 | 52,960 | 52,960 |
| $R^2$ | 0.263 | 0.264 | 0.661 | 0.663 | 0.507 | 0.508 |

*Notes*: Robust standard errors in parentheses; ** p<0.01, * p<0.05, † p<0.10.

**Table A13. Rule out Alternative Explanations: Price Discount**

| | (1) |
|---|---|
| | No. of reviews containing words indicative of discount |
| *Outbreak* | 0.082 |
| | (0.054) |
| ***Chinese* × *Outbreak*** | **-0.027** |
| | **(0.137)** |
| *Recovery* | -0.807** |
| | (0.038) |
| ***Chinese* × *Recovery*** | **0.115** |
| | **(0.090)** |
| *Constant* | -2.819** |
| | (0.016) |
| Monthly FE | √ |
| Restaurant FE | √ |
| Observations | 347,208 |
| No. of restaurants | 6,789 |
| $R^2$ | 0.070 |

*Notes*: Robust standard errors are in parentheses; ** p<0.01, * p<0.05, † p<0.10.

**Table A14. Rule out Alternative Explanations: Restaurant Closures**

| | (1)<br>num_visit | (2)<br>sales | (3)<br>num_visit | (4)<br>sales |
|---|---|---|---|---|
| *Outbreak* | 0.050** | 0.011 | 0.046** | 0.017 |
| | (0.017) | (0.024) | (0.018) | (0.021) |
| ***Chinese* × *Outbreak*** | **-0.000** | **0.015** | **0.044** | **0.049** |
| | **(0.039)** | **(0.056)** | **(0.041)** | **(0.038)** |
| *Recovery* | -0.062** | -0.369** | -0.075** | -0.369** |
| | (0.016) | (0.034) | (0.019) | (0.030) |
| ***Chinese* × *Recovery*** | **-0.104*** | **-0.135*** | **-0.106*** | **-0.078*** |
| | **(0.052)** | **(0.055)** | **(0.053)** | **(0.035)** |
| *Constant* | 3.045** | 5.667** | 3.184** | 5.854** |
| | (0.009) | (0.018) | (0.010) | (0.016) |
| Monthly FE | √ | √ | √ | √ |
| Restaurant FE | √ | √ | √ | √ |
| Control for operation hours | √ | √ | √ | √ |
| Observations | 299,970 | 299,860 | 208,735 | 208,748 |
| R2 | 0.604 | 0.532 | 0.649 | 0.527 |

*Notes*: Robust standard errors are in parentheses; ** p<0.01, * p<0.05, † p<0.10.

**Table A15. Rule out Alternative Explanations: Take-out vs. Dine-in**

| | (1)<br>No. of takeout | (2)<br>No. of dine-in | (3)<br>Ratio of No. of takeout to No. of dine-in |
|---|---|---|---|
| *Outbreak* | 0.043** | 0.022 | 0.190** |
| | (0.014) | (0.017) | (0.055) |
| ***Chinese* × *Outbreak*** | **-0.051*** | **-0.004** | **-0.526**** |
| | **(0.022)** | **(0.034)** | **(0.099)** |
| *Recovery* | 0.345** | 0.575† | -0.631 |
| | (0.131) | (0.307) | (0.627) |
| ***Chinese* × *Recovery*** | **-0.118**** | **-0.123**** | **-0.448**** |
| | **(0.031)** | **(0.047)** | **(0.120)** |
| *Constant* | 3.970** | 3.163** | 3.547** |
| | (0.068) | (0.133) | (0.320) |
| Monthly FE | √ | √ | √ |
| Restaurant FE | √ | √ | √ |
| Observations | 279,866 | 277,742 | 249,347 |
| $R^2$ | 0.838 | 0.721 | 0.492 |

*Notes*: Robust standard errors are in parentheses; ** p<0.01, * p<0.05, † p<0.10.

**Table A16. Rule out Alternative Explanations: Customers' Self-Selection**

| | (1) Rating | (2) Rating | (3) Rating | (4) Rating | (5) Rating | (6) Rating | (7) Rating | (8) Rating | (9) Premium in rating | (10) Premium in rating | (11) Premium in rating | (12) Premium in rating | (13) Premium in rating | (14) Premium in rating | (15) Premium in rating | (16) Premium in rating |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Outbreak* | -0.004 | -0.008 | -0.036 | -0.001 | -0.006 | -0.044+ | -0.047 | -0.030 | 0.009 | 0.007 | 0.003 | 0.006 | 0.006 | 0.004 | -0.017 | 0.001 |
| | (0.019) | (0.020) | (0.033) | (0.019) | (0.019) | (0.024) | (0.032) | (0.039) | (0.017) | (0.018) | (0.032) | (0.017) | (0.017) | (0.023) | (0.030) | (0.039) |
| ***Chinese* × *Outbreak*** | **0.002** | **-0.002** | -0.060 | -0.012 | -0.006 | 0.001 | -0.026 | -0.035 | **-0.001** | **-0.019** | -0.102* | -0.020 | -0.018 | -0.040 | -0.040 | -0.071 |
| | **(0.038)** | **(0.042)** | (0.057) | (0.037) | (0.037) | (0.049) | (0.055) | (0.060) | **(0.035)** | **(0.037)** | (0.052) | (0.033) | (0.033) | (0.045) | (0.050) | (0.056) |
| *Recovery* | 0.000 | 0.000 | 0.063* | 0.063** | 0.060** | 0.050** | 0.025 | 0.023 | 0.000 | 0.000 | 0.126** | 0.092** | 0.090** | 0.083** | 0.071** | 0.073** |
| | (0.000) | (0.000) | (0.025) | (0.014) | (0.014) | (0.018) | (0.024) | (0.028) | (0.000) | (0.000) | (0.023) | (0.012) | (0.012) | (0.017) | (0.022) | (0.027) |
| ***Chinese* × *Recovery*** | **0.055**** | **0.060**** | 0.084* | 0.053* | 0.059* | 0.076* | 0.080* | 0.103* | **0.090**** | **0.090**** | 0.102** | 0.065** | 0.065** | 0.097** | 0.121** | 0.114** |
| | **(0.015)** | **(0.015)** | (0.041) | (0.026) | (0.026) | (0.037) | (0.041) | (0.043) | **(0.013)** | **(0.014)** | (0.035) | (0.022) | (0.021) | (0.032) | (0.037) | (0.039) |
| *Constant* | 0.074** | 0.083** | 3.962** | 3.889** | 3.915** | 3.955** | 3.996** | 3.887** | 0.089** | 0.097** | -0.631** | -0.511** | -0.509** | -0.580** | -0.585** | -0.639** |
| | (0.027) | (0.031) | (0.010) | (0.006) | (0.007) | (0.009) | (0.011) | (0.013) | (0.023) | (0.026) | (0.009) | (0.005) | (0.006) | (0.008) | (0.010) | (0.012) |
| Monthly FE | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ |
| Restaurant FE | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ |
| Customer FE | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ |
| Observations | 177,583 | 131,145 | 39,208 | 227,611 | 210,071 | 77,024 | 42,532 | 30,564 | 177,583 | 131,145 | 39,208 | 227,611 | 210,071 | 77,024 | 42,532 | 30,564 |
| $R^2$ | 0.613 | 0.606 | 0.576 | 0.643 | 0.614 | 0.567 | 0.565 | 0.624 | 0.491 | 0.482 | 0.492 | 0.524 | 0.497 | 0.458 | 0.471 | 0.508 |

*Notes*: Robust standard errors are in parentheses; ** p<0.01, * p<0.05, † p<0.10.

**Table A17. Rule out Alternative Explanations: Chain vs. Non-Chain Restaurants**

| | (1) Patronage | (2) Rating | (3) Premium in Rating | (4) Patronage | (5) Rating | (6) Premium in Rating |
|---|---|---|---|---|---|---|
| *Outbreak* | 0.017 | -0.003 | 0.007 | 0.023† | 0.005 | 0.011 |
| | (0.013) | (0.020) | (0.018) | (0.013) | (0.020) | (0.018) |
| *Recovery* | -0.536** | 0.071** | 0.092** | -0.536** | 0.080** | 0.094** |
| | (0.013) | (0.015) | (0.013) | (0.012) | (0.015) | (0.013) |
| *Chinese* × *Outbreak* | -0.137** | -0.008 | -0.014 | -0.139** | -0.008 | -0.012 |
| | (0.039) | (0.042) | (0.037) | (0.036) | (0.040) | (0.036) |
| *Chinese* × *Recovery* | -0.063† | 0.037 | 0.069** | -0.075* | 0.044 | 0.081** |
| | (0.035) | (0.030) | (0.025) | (0.033) | (0.029) | (0.024) |
| *Outbreak* × *Chain_Store* | 0.013 | 0.023 | 0.029 | | | |
| | (0.017) | (0.022) | (0.020) | | | |
| Recovery × *Chain_Store* | 0.007 | -0.027† | -0.012 | | | |
| | (0.017) | (0.015) | (0.013) | | | |
| *Chinese* × *Outbreak* × *Chain_Store* | 0.009 | 0.007 | -0.009 | | | |
| | (0.073) | (0.091) | (0.087) | | | |
| ***Chinese* ×*Recovery* × *Chain_Store*** | **-0.015** | **0.083** | **0.019** | | | |
| | **(0.063)** | **(0.061)** | **(0.053)** | | | |
| *Outbreak* × *Chain_Store_Scale* | | | | -0.003 | -0.000 | 0.008 |
| | | | | (0.005) | (0.010) | (0.009) |
| *Recovery* × *Chain_Store_Scale* | | | | 0.006 | -0.028** | -0.009 |
| | | | | (0.033) | (0.007) | (0.006) |
| *Chinese* × *Outbreak* × *Chain_Store_Scale* | | | | 0.004 | -0.002 | -0.013 |
| | | | | (0.005) | (0.049) | (0.043) |
| ***Chinese* ×*Recovery* × *Chain_Store_Scale*** | | | | **0.026** | **0.018** | **-0.028** |
| | | | | **(0.025)** | **(0.034)** | **(0.029)** |
| *Constant* | -0.427** | 3.910** | -0.510** | -0.427** | 3.910** | -0.510** |
| | (0.005) | (0.007) | (0.006) | (0.005) | (0.007) | (0.006) |
| Monthly FE | √ | √ | √ | √ | √ | √ |
| Restaurant FE | √ | √ | √ | √ | √ | √ |
| Customer FE | | √ | √ | | √ | √ |
| Observations | 1,389,372 | 204,489 | 204,489 | 1,389,372 | 204,489 | 204,489 |
| No. of restaurants | 27,212 | 20,148 | 20,148 | 27,212 | 20,148 | 20,148 |
| No. of customers | | 52,960 | 52,960 | | 52,960 | 52,960 |
| $R^2$ | 0.263 | 0.617 | 0.500 | 0.263 | 0.617 | 0.500 |

*Notes*: Robust standard errors are in parentheses; ** p<0.01, * p<0.05, † p<0.10.

**Table A18. Rule out Alternative Explanations: Competition**

| | (1)<br>Patronage | (2)<br>Rating | (3)<br>Premium in Rating |
|---|---|---|---|
| *Outbreak* | 0.036 | -0.032 | -0.049 |
| | (0.023) | (0.049) | (0.045) |
| ***Chinese × Outbreak*** | **-0.128**** | **-0.011** | **-0.038** |
| | **(0.036)** | **(0.055)** | **(0.051)** |
| *Recovery* | -0.545** | 0.045 | 0.099** |
| | (0.021) | (0.034) | (0.032) |
| ***Chinese × Recovery*** | **-0.058†** | **0.089*** | **0.115**** |
| | **(0.033)** | **(0.037)** | **(0.033)** |
| *Constant* | -0.622** | 3.864** | -0.571** |
| | (0.012) | (0.015) | (0.014) |
| Monthly FE | √ | √ | √ |
| Restaurant FE | √ | √ | √ |
| Customer FE | | √ | √ |
| Observations | 448,179 | 35,048 | 35,048 |
| No. of restaurants | 8,799 | 5,242 | 5,242 |
| No. of customers | | 11,744 | 11,744 |
| $R^2$ | 0.245 | 0.698 | 0.600 |

*Notes*: Robust standard errors are in parentheses; ** p<0.01, * p<0.05, † p<0.10.

**Table A19. Export and Import between U.S. and China in 2020 (in million dollars)**

| **Month** | **Exports** | **Imports** | **Balance** |
|---|---|---|---|
| January | 7,153.7 | 33,173.3 | -26,019.6 |
| February | 6,828.4 | 22,720.9 | -15,892.5 |
| March | 7,900.4 | 19,789.1 | -11,888.7 |
| April | 8,624.4 | 30,922.8 | -22,298.4 |
| May | 9,671.6 | 36,551.7 | -26,880.0 |
| June | 9,236.6 | 37,495.1 | -28,258.4 |
| July | 9,088.3 | 40,658.0 | -31,569.6 |
| August | 10,961.7 | 40,791.5 | -29,829.9 |
| September | 11,497.7 | 41,194.3 | -29,696.6 |
| October | 14,773.1 | 44,779.2 | -30,006.1 |
| November | 14,219.7 | 44,839.3 | -30,619.6 |
| December | 14,529.6 | 41,833.7 | -27,304.1 |
| Total | 124,485.4 | 434,749.0 | -310,263.5 |

**Table A20. Alternative Definitions of Outbreak and Recovery Periods**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Patronage | Patronage | Patronage | Rating | Rating | Rating | Premium in Rating | Premium in Rating | Premium in Rating |
| *Outbreak* | -0.764** | -1.046** | 0.028* | 0.069 | 0.019 | 0.012 | 0.118 | 0.081 | 0.028 |
| | (0.050) | (0.058) | (0.011) | (0.102) | (0.093) | (0.020) | (0.086) | (0.091) | (0.018) |
| ***Chinese* × *Outbreak*** | **-0.133**** | **-0.135**** | **-0.135**** | **0.012** | **0.014** | **-0.021** | **-0.019** | **-0.020** | **-0.050** |
| | **(0.028)** | **(0.028)** | **(0.032)** | **(0.032)** | **(0.032)** | **(0.038)** | **(0.029)** | **(0.029)** | **(0.034)** |
| *Recovery* | -0.448** | -0.448** | -0.449** | -0.015 | -0.014 | -0.014 | 0.060* | 0.060* | 0.060* |
| | (0.016) | (0.016) | (0.016) | (0.029) | (0.029) | (0.029) | (0.026) | (0.026) | (0.026) |
| ***Chinese* × *Recovery*** | **-0.089**** | **-0.088**** | **-0.067*** | **0.074*** | **0.072*** | **0.063*** | **0.058*** | **0.058*** | **0.055*** |
| | **(0.031)** | **(0.031)** | **(0.029)** | **(0.030)** | **(0.030)** | **(0.028)** | **(0.026)** | **(0.026)** | **(0.024)** |
| *Constant* | -0.264** | -0.858** | -0.429** | 3.932** | 4.001** | 3.946** | 0.523** | 0.470** | 0.500** |
| | (0.014) | (0.019) | (0.007) | (0.029) | (0.034) | (0.013) | (0.024) | (0.031) | (0.012) |
| Monthly FE | √ | √ | √ | √ | √ | √ | √ | √ | √ |
| Restaurant FE | √ | √ | √ | √ | √ | √ | √ | √ | √ |
| Customer FE | | | | √ | √ | √ | √ | √ | √ |
| Observations | 1,385,128 | 1,385,128 | 1,385,128 | 179,110 | 179,110 | 179,110 | 179,110 | 179,110 | 179,110 |
| No. of restaurants | 30,924 | 30,924 | 30,924 | 19,145 | 19,145 | 19,145 | 19,145 | 19,145 | 19,145 |
| No. of customers | | | | 47,190 | 47,190 | 47,190 | 47,190 | 47,190 | 47,190 |
| $R^2$ | 0.264 | 0.264 | 0.264 | 0.623 | 0.623 | 0.623 | 0.510 | 0.510 | 0.510 |

*Notes*: Robust standard errors are in parentheses; ** p<0.01, * p<0.05, † p<0.10.

**Table A21. Test for Other Ethnic Restaurants**

| | (1) | (2) | (3) |
|---|---|---|---|
| | Patronage (Latin) | Rating (Latin) | Premium in Rating (Latin) |
| *Outbreak* | 0.016 | -0.002 | -0.001 |
| | (0.012) | (0.020) | (0.018) |
| ***Ethnic* × *Outbreak*** | **0.006** | **-0.025** | **-0.098†** |
| | **(0.063)** | **(0.066)** | **(0.057)** |
| *Recovery* | -0.547** | 0.068** | 0.099** |
| | (0.011) | (0.015) | (0.013) |
| ***Ethnic* ×*Recovery*** | **0.014** | **0.034** | **-0.016** |
| | **(0.053)** | **(0.045)** | **(0.039)** |
| *Constant* | -0.506** | 3.912** | -0.509** |
| | (0.005) | (0.007) | (0.006) |
| Monthly FE | √ | √ | √ |
| Restaurant FE | √ | √ | √ |
| Customer FE | | √ | √ |
| Observations | 1,372,826 | 188,149 | 188,149 |
| No. of restaurants | 26,887 | 19,643 | 19,643 |
| No. of customers | | 48,554 | 48,554 |
| $R^2$ | 0.255 | 0.620 | 0.503 |

*Notes*: Robust standard errors are in parentheses; ** p<0.01, * p<0.05, † p<0.10.

**Table A22. Results of Placebo Test**

| | (1) | (2) | (3) |
|---|---|---|---|

| | Patronage (Placebo) | Rating (Placebo) | Premium in Rating (placebo) |
|---|---|---|---|
| *Outbreak_Placebo* | 0.012 | -0.021 | -0.011 |
| | (0.012) | (0.021) | (0.019) |
| ***Chinese* × *Outbreak_Placebo*** | **-0.014** | **-0.038** | **-0.015** |
| | **(0.032)** | **(0.047)** | **(0.041)** |
| *Recovery_Placebo* | 0.003 | -0.027 | -0.014 |
| | (0.012) | (0.021) | (0.020) |
| ***Chinese* × *Recovery_Placebo*** | **0.037** | **0.010** | **-0.005** |
| | **(0.027)** | **(0.022)** | **(0.021)** |
| *Constant* | -0.254** | 3.885** | -0.522** |
| | (0.004) | (0.007) | (0.006) |
| Monthly FE | √ | √ | √ |
| Restaurant FE | √ | √ | √ |
| Customer FE | | √ | √ |
| Observations | 1,429,241 | 272,007 | 272,007 |
| No. of restaurants | 32,653 | 21,898 | 21,898 |
| No. of customers | | 69,990 | 69,990 |
| $R^2$ | 0.306 | 0.596 | 0.483 |

*Notes*: Robust standard errors in parentheses; ** p<0.01, * p<0.05, † p<0.10.

**Table A23. Tests of Review Bombing**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | 1-star rating | 5-star rating | low rating | high rating | Standard deviation of rating |
| *Outbreak* | 0.009* | -0.008 | 0.005 | -0.005 | 0.025 |
| | (0.004) | (0.005) | (0.005) | (0.005) | (0.019) |
| ***Chinese* × *Outbreak*** | **-0.029**** | **0.030*** | **-0.016** | **0.016** | **-0.087+** |
| | **(0.009)** | **(0.013)** | **(0.012)** | **(0.012)** | **(0.047)** |
| *Recovery* | 0.010** | 0.047** | -0.016** | 0.016** | -0.021 |
| | (0.003) | (0.004) | (0.003) | (0.003) | (0.015) |
| ***Chinese* × *Recovery*** | **-0.023**** | **0.025**** | **-0.018*** | **0.018*** | **-0.040** |
| | **(0.006)** | **(0.008)** | **(0.008)** | **(0.008)** | **(0.040)** |
| *Constant* | 0.160** | 0.468** | 0.344** | 0.656** | 0.915** |
| | (0.001) | (0.002) | (0.002) | (0.002) | (0.007) |
| Monthly FE | √ | √ | √ | √ | √ |
| Restaurant FE | √ | √ | √ | √ | √ |
| Observations | 243,165 | 243,165 | 243,165 | 243,165 | 61,473 |
| $R^2$ | 0.306 | 0.257 | 0.288 | 0.288 | 0.227 |

*Notes*: Robust standard errors in parentheses; ** p<0.01, * p<0.05, † p<0.10.

**Table A24. Examples of Mapping: Premium_in_Rating and Rating**

| Premium in rating | Rating | Compound | Compound rescaled | Review text |
|---|---|---|---|---|
| 3.9818 | 5 | -0.9909 | 0.0182 | I just ate here alone. I never actually sit down at a restaurant and eat alone but I did it, gave it a shot. It's been a weird day and I was feeling reckless. You know what? It's pretty fucking boring. I'm just stuck there alone with my thoughts, all anxious and shit. All the dark corridors of my brain leaking out and infesting my every being. It was truly an awful experience. I'll never eat a meal without watching or looking at some stupid shit on the internet ever again.<br>Anyways, I got an al pastor burrito and it was solid dude, all creamy, flavorful and whatnot. I did bite into a giant chunk of gristle but all it did was remind me of the fucks who complain about that shit. Like sorry the chef didn't perfectly trim the giant fucking pork shoulder. Just spit it out and move on with your life. I swear some people encounter some hard fat or connective tissue at restaurants and equate it to stepping on a nail.<br>The staff was awesome too. Even thought the place was empty they still were totally on the ball and friendly.<br>If this place got a liquor license and started slingin drinks I'd plant my pasty white ass there every single weekend. As of now, it'll probably just be a take-out place, if I'm alone that is. |
| 2 | 5 | 0 | 3 | This is my new go-to spot for milk tea and snacks! T4 fills a void in the Bethany area. |
| 1.9886 | 4 | -0.4943 | 2.0114 | Go there at 9am on Saturday morning and there was already a few groups waiting outside. Went inside and put my name on the list. Only waited about 2 minutes before we were seated at the bar. I ordered the Chile Verde with a side of hash browns and scrambled eggs. Order of Chile verde was delicious, but so large that I wasn't able to finish it all. Hash browns weren't the greatest. Ketchup was more of a thick, tomato purée. |
| 0 | 3 | 0 | 3 | Relatively small portions of flavorful northern Thai food. Not necessarily the place for having a feast... |
| -2.08 | 2 | 0.54 | 4.08 | Food and coffee looks really good! Not open at 9am on Saturday so I'm walking somewhere else |
| -3.9772 | 1 | 0.9886 | 4.9772 | I'm working in Boston for awhile, so I figured I'd check out some of the local restaurants. This place stuck out to me because of the name. My first wife's name was Regina. She broke my heart and took me for everything, but I wasn't going to let that ruin my good time. |

| | | | | |
|---|---|---|---|---|
| | | | | This place is great. A classic Boston institution. There's lots of fun stuff on the walls and I bet Regina would have loved this place. Her favorite pizza was Hawaiian and I would always make fun of her for it. "Pineapples don't belong on pizza!" I would always joke.<br>I ordered the sausage pizza and it was amazing. A light-yet somewhat doughy crust, perfectly cooked, a sweet and savory red sauce, and the sausage was spiced perfectly.<br>After dinner I decided to buy a shirt for Regina because it had her name on it. After working up the nerve I decided to text her a picture of it. It seemed that she blocked my number. I hate this place. I hate Boston. I want to go home. |

**Table A25. Alternative Packages to Conduct Sentiment Analyses**

| | (1) | (2) |
|---|---|---|
| | Premium in Rating (TextBlob) | Premium in Rating (AFINN) |
| *Outbreak* | 0.005 | 0.000 |
| | (0.016) | (0.018) |
| ***Chinese* × *Outbreak*** | **-0.005** | **-0.011** |
| | **(0.033)** | **(0.036)** |
| *Recovery* | 0.063** | 0.069** |
| | (0.012) | (0.014) |
| ***Chinese* × *Recovery*** | **0.049*** | **0.054*** |
| | **(0.022)** | **(0.025)** |
| *Constant* | 0.393** | 1.464** |
| | (0.006) | (0.006) |
| Monthly FE | √ | √ |
| Restaurant FE | √ | √ |
| Customer FE | √ | √ |
| Observations | 213,664 | 213,664 |
| $R^2$ | 0.585 | 0.609 |

*Notes*: Robust standard errors in parentheses; ** p<0.01, * p<0.05, † p<0.10.

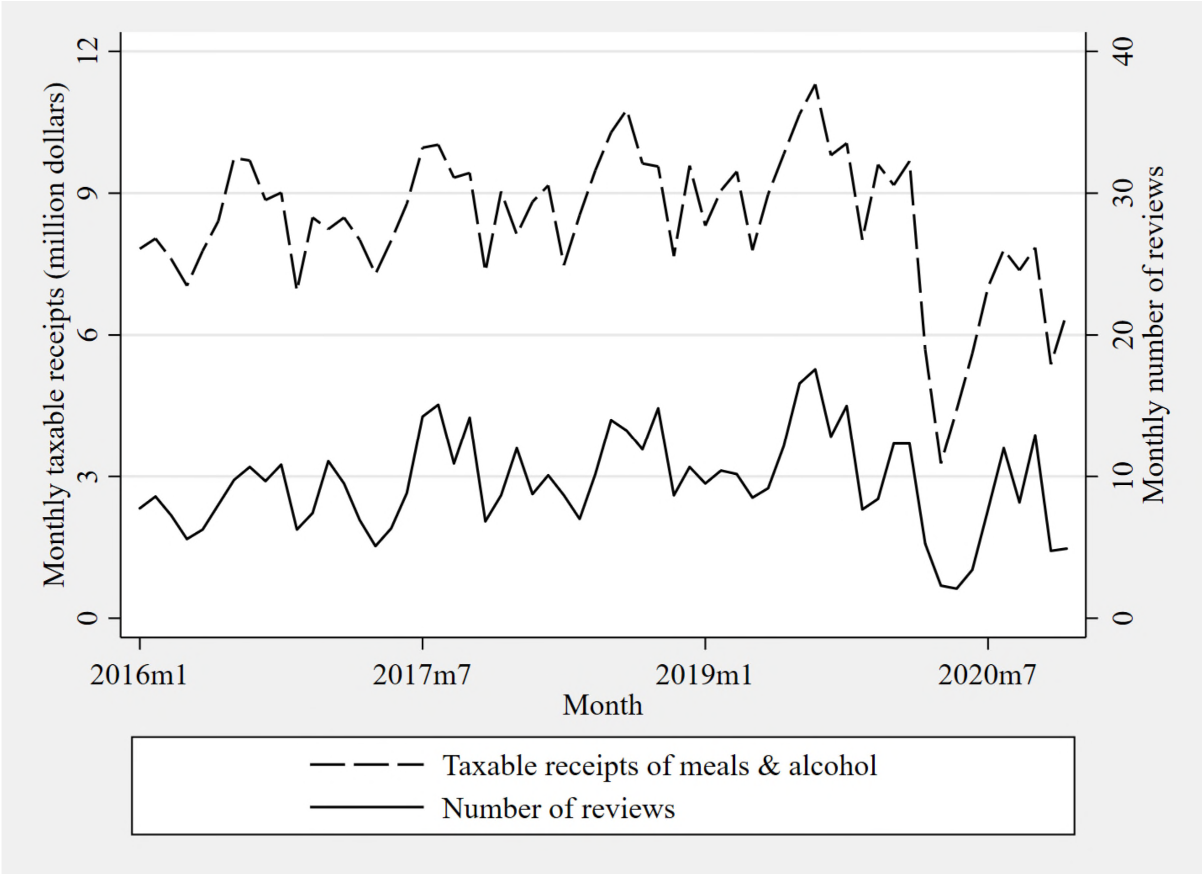


**Figure A1. Monthly Taxable Receipts and Number of Reviews**

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