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Consumer Sentiment Towards Asians in the Early Days of the COVID-19 Pandemic

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Abstract

The researchers revisit the early months of the COVID-19 pandemic to examine whether restaurant foot traffic reveals changes in sentiment towards ethnic groups. Their findings show reduced demand for dining at Asian restaurants located inside Asian enclaves, while outside enclaves, the decline in visits to Asian restaurants was comparable to non-Asian restaurants. In contrast, Italian restaurant enclaves did not experience similar declines in foot traffic after news of the outbreak in Italy and the first U.S. case linked to travel to Italy. The researchers also find suggestive evidence that the shift in consumption was associated with elevated negative sentiment towards Asians rather than efforts to avoid exposure to international travelers.

1 Introduction

Consumer sentiment towards Asian businesses gained significant attention during the Covid-19 pandemic, as media reports highlighted sharp declines in foot traffic to Asian restaurants, both within and outside of Chinatowns.[1] Some attributed these declines to heightened negative racial sentiment, supported by the rise in inflammatory rhetoric (Matthew Costello et al. (2021)) and hate incidents targeting Asian Americans (Gover et al. (2020), Tessler et al. (2020)). However, an alternative explanation is that consumers avoided dining out generally to reduce exposure to the virus (Chong et al. (2023)). To better understand this demand shock, we analyze foot traffic to East Asian and Southeast Asian restaurants before and after the onset of the pandemic.

This research question is motivated, in part, by the observation that a rise in anti-Asian sentiment may not directly translate into market disparities. Economic theory suggests that economic outcomes are determined by the prejudice of the marginal discriminator, an employer, co-worker, or customer who chooses to interact with the discriminated-against group (Becker (1957)). If Covid-19 activated anti-Asian sentiment among those who never previously engaged with Asian small businesses, the impacts on economic outcomes might be limited. Our analysis of foot traffic to East Asian and Southeast Asian restaurants before and after the onset of the virus is meaningful because it reveals changes in the decision-making of those who were previously willing to patronize and interact with Asian restaurants.

Our analysis focuses on the period between the first confirmed Covid-19 case in the United States and the first state-level stay-at-home order, which we refer to as our Focal Period. Prior to the first U.S. case, dining out was unlikely to be perceived as a significant health risk. After the first stay-at-home order, the economy experienced unprecedented shocks, and recent research suggests that such broad, structural changes can generate substantial disparate impacts by race and ethnicity (Bayer and Charles (2018), Derenoncourt and Montialoux (2021)).[2] The Focal Period is arguably when shifts in foot traffic most reflected

[1]For example, a PBS News Hour article from December 2020 was titled *Racism targets Asian food, business during Covid-19 pandemic* (link), and in a February 26, 2020 interview on *All Things Considered*, Kevin Chan, a San Francisco Chinatown business owner, reported a 70-80% drop in business due to coronavirus fears (`https://n.pr/3ASRB7G`).

[2]For example, narrower streets in Boston's Chinatown made it more difficult to create outdoor dining spaces than in other neighborhoods. See this article here.

changes in demand-side sentiment rather than supply-side adjustments.[3]

We use SafeGraph foot traffic data that tracks visits to places of interest via cellphone pings. This data is appealing for several reasons. It is longitudinal, allowing us to account for restaurant features that remained constant in the early months of the pandemic through restaurant fixed effects. Additionally, the data includes ethnicity tags that enable us to identify the cuisine's ethnicity for each restaurant. This is particularly valuable as ethnic identity is not typically observed in data for other types of small businesses (e.g., legal offices, dentists, and florists). The ethnicity tags are detailed, allowing us to disaggregate Asian cuisine into Thai, Vietnamese, Korean, Japanese, and Chinese categories, as well as identify non-Asian cuisines (e.g., Italian, Mexican, and Greek). For the sake of brevity, we will refer to East Asian and Southeast Asian cuisines collectively as Asian, and all other ethnic groups as non-Asian, hereafter.[4]

Another feature of the data is that we can observe the neighborhood in which each restaurant is located. Using latitude and longitude coordinates and census block group information for all restaurants, we construct a neighborhood-level isolation index, a standard measure of residential segregation, to determine whether a restaurant is located in an ethnic restaurant enclave (Denton and Massey (1988)). This is valuable in light of economic research demonstrating that subgroups *within* an ethnic group with attributes (e.g., skin tone and vernacular) more distant from those of the ingroup can experience relatively worse outcomes (Grogger (2011), Kreisman and Rangel (2015), Honoré and Hu (2022)). Ethnic restaurant enclaves provide an opportunity to explore potential *intragroup* effects related to the perceived assimilation and authenticity of these businesses.

Our analysis reveals that, outside of Chinese restaurant enclaves, both non-Asian and

[3]Aggregate statistics of flight patterns, subway usage, restaurant visits, and other economic activity suggest that business was conducted more or less "as usual" in early 2020. Chetty et al. (2020) documents that consumer spending, employment rates, educational progress, and small business revenue were fairly stable in January and February before abruptly pivoting in mid-March due to widespread stay-at-home orders. Similar patterns are shown in air flights, MTA subway ridership, and daily travel statistics collected by the Bureau of Transportation Statistics (BTS).

[4]We anticipate that spillover effects most likely affect ethnic cuisines perceived to be most similar to Chinese cuisine. Recent computer science research utilizes machine learning techniques trained on recipe data from popular sources like AllRecipes, Food Network, Epicurious, and TarlaDalal to analyze and cluster international cuisines (Hanai et al. (2015), Anupam Jain et al. (2015), Singh and Bagler (2018), Ozaki et al. (2017)). This research distinguishes Indian cuisine from Southeast and East Asian cuisines based on flavor profiles, spices, and staple ingredients.

Asian restaurants experienced similar declines in foot traffic of approximately 15% during the Focal Period. These findings do not support the narrative that the decline in foot traffic during this time was specific to Asian restaurants.

However, within highly isolated Chinese restaurant enclaves, Asian restaurants experienced significantly sharper declines in foot traffic compared to their counterparts outside these enclaves. There is some evidence suggesting that consumers shifted towards non-Asian restaurants within more isolated Chinese restaurant enclaves, although these differential effects are not precisely estimated. Other ethnic cuisines, including Mediterranean, Greek, Mexican, Italian, and Indian restaurants, do not exhibit similar enclave effects. The absence of such effects in Italian enclaves is particularly interesting, given that Italy also experienced a coronavirus outbreak during the Focal Period. These findings indicate that the declines in foot traffic to Chinese enclaves were not driven by characteristics common across all restaurant enclaves. Our results align with Honoré and Hu (2022), who found that foreign-born Asian Americans experienced greater labor market distress during the Covid-19 pandemic, suggesting an important role for perceived assimilation.

We explore two potential explanations for these results. First, consumers may have associated dining in Chinese enclaves with a higher risk of virus transmission, either correctly or incorrectly. If Chinese restaurant enclaves received greater foot traffic from recent international travelers, this could explain the sharper decline in visits, as exposure to international travelers was believed to be a primary transmission channel early in the pandemic.[5] Alternatively, the coronavirus's arrival may have activated negative sentiment towards Asian Americans, particularly those perceived as more culturally distant from mainstream America. An early theory about the virus's origins, linking it to bat sales in Wuhan's wet markets, could have increased the salience of negative stereotypes associated with more authentic Chinese marketplaces in America.

We leverage metropolitan area-level variation in Google search intensity for the term "Kung Flu" as a measure of shifts in attitudes towards Asians. This measure is motivated by the seminal work of Allport (1979), which posits that antilocution, negative comments

[5]This idea was echoed by public officials early in the pandemic. For example, on February 25, 2020, San Francisco's mayor officially proclaimed a state of emergency, even without confirmed cases. Veronica Vien, Public Information Officer at San Francisco Department of Public Health, explained to NPR, "Given the amount of travel between San Francisco and China, we understand a confirmed case in San Francisco is possible."

regarding an outgroup often made offhand or in jest, is an early form of prejudice. To measure potential exposure to the virus, we construct a metropolitan area-level measure of the share of visits to restaurants from recent international travelers prior to the arrival of the virus. We then examine which of these features—anti-Asian sentiment or potential virus exposure—explains more of the metropolitan area-level variation in the enclave effects.

Our analysis reveals that metropolitan area-level interest in "Kung Flu" is a strong predictor of the enclave effects during the Focal Period. A 1 standard deviation increase in search intensity for "Kung Flu" is associated with approximately a 6 percentage point additional decrease in visits to Asian restaurants, *ceteris paribus*. This relationship persists even after controlling for cross-metropolitan area differences in Asian residential segregation and population share. When comparing search interest in "Kung Flu" with exposure to recent international travelers in enclaves, only our measure of antilocution emerges as a strong predictor of the enclave effects. This result is primarily driven by metropolitan areas previously associated with below-average racial prejudice. While the estimating variation is not random, these findings suggest that our results more likely reflect changes in racial sentiment rather than efforts to minimize exposure to recent travelers.

Our findings build on research examining factors that contributed to the activation of anti-Asian sentiment during the Covid-19 pandemic, such as pathogen avoidance, media coverage, and online memes (Makhanova (2022), Hill (2021)). Our study aligns closely with work investigating the disparate impacts of Covid-19 on market outcomes for the Asian community (Luca et al. (2023), Honoré and Hu (2022), Qin et al. (2023), Huang et al. (2023)). We contribute to this literature in several ways: by focusing on the Focal Period before major structural economic changes occurred, exploring intragroup effects, and measuring shifts in sentiment through antilocution rather than static measures of Asian bias.

Our study also aligns with recent research showing that racial attitudes are not fixed and can be influenced by external factors. For example, incendiary media (Ang (2023), Mueller-Smith (2014)) and inflammatory rhetoric (Grosjean et al. (2023)) have been shown to incite harmful behaviors toward targeted minority groups. Similarly, international crises have historically acted as catalysts for heightened negative sentiment toward ethnic groups associated with the nations involved. For instance, German Americans during World War I (Moser (2012)), Japanese Americans during World War II (CWRIC (1997)), and Muslim

Americans after 9/11 (Gould and Klor (2016)) all experienced elevated discrimination.[6] Our findings support the notion that external events, such as the Covid-19 pandemic, can amplify negative racial sentiment, leading to measurable social and economic consequences.

The remainder of the paper is organized as follows. In Section 2, we outline a conceptual framework to organize our empirical analysis. In Section 3, we provide a few validation exercises of the SafeGraph foot traffic data. In Section 4, we present the empirical model. In Section 5, we present the main results. In Section 6, we discuss potential explanations, and finally, we conclude.

2 Conceptual Framework

2.1 Economic Paradigms of Discrimination

Our empirical analysis is informed by the two main economic paradigms of discrimination: preference-based (or taste-based) and belief-based (or statistical) bias. There is extensive research on how biased beliefs update, either correctly or incorrectly, as economic actors receive new information (Bordalo et al. (2016), Bohren et al. (2019), Bohren et al. (2023), Coate and Loury (1993), Arrow (1973)). In contrast, preference-based bias is typically modeled as a static construct, not subject to change. However, recent research challenges this view, suggesting that racial sentiment can be activated by external shocks and that such activation can lead to harm in important social outcomes (Mueller-Smith (2014), Grosjean et al. (2023), Ang (2023)). If this possibility holds, then a key question for our study is whether the Covid-19 pandemic acted as a catalyst for activating anti-Asian sentiment.

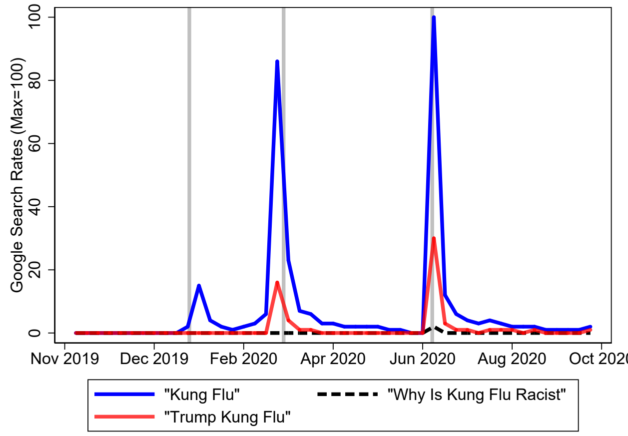
Google Search Trends indicate that rhetoric surrounding Asians underwent sharp changes during the early days of the Covid-19 pandemic.[7] Figure 1a presents the time series for

[6]Examples include declines in the use of German-sounding names and cultural products during World War I (Moser (2012)) and anecdotes of bullying against Russian-speaking children during the Russia-Ukraine War, as reported by the New York Times.

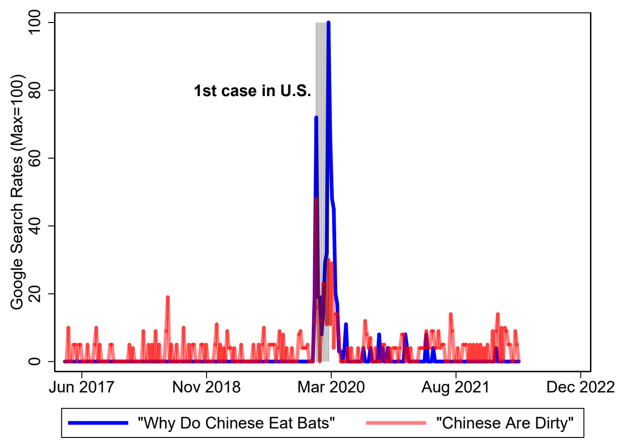
[7]Google Trends offers valuable insights into public interest by providing real-time, large-scale data on search queries across diverse topics and regions, reflecting current concerns and information-seeking behavior of internet users. However, it has several limitations that should be considered when interpreting the data; for example, Google Trends obscures absolute search counts, which makes it challenging to determine the actual size or volume of a topic, there are potential selection issues since the data only includes Google users with internet access, there is a lack of context regarding user searches as the intent behind a query is often unclear. Despite these limitations, Google Trends remains a powerful tool for understanding public interest

Google search intensity for the terms “Kung Flu,” “Why is Kung Flu Racist,” and “Trump Kung Flu.” The three vertical lines mark key dates: the first positive COVID-19 case in the United States, the first stay-at-home order, and Donald Trump’s political rally in Tulsa, Oklahoma. Search interest for “Kung Flu” began to rise shortly after the first documented U.S. case, well before the term became associated with President Trump. While this January increase is smaller than later spikes, it is significant that it occurred without a concurrent rise in searches for “Trump Kung Flu” or “Why is Kung Flu Racist,” suggesting that the initial increase was not primarily driven by political interest or curiosity about the term’s contentiousness. Importantly, Google Search Trends reflect normalized rates rather than absolute levels of searches, meaning the observed spikes indicate a higher proportion of searches rather than an overall increase in search activity.

and trends when used in conjunction with other data sources and interpreted with caution.



(a) Google Search Intensity for "Kung Flu" and Related Terms



(b) Negative Associations Between Virus Origin Hypothesis and Race

Notes: Google search rate intensity is relative to the week of the maximum search rate which is normalized to 100. All other values, including search rates of other search terms, are relative to this maximum. Thus, within a time series, a value of, say, 80 at one date and 40 at a later date implies that search rates fell by half. Comparisons can be made across time series, but Google Search Trends allows for up to 5 search terms at a time. In Panel (b), the blue and red lines show Google Search Rates for the search terms "Why Do Chinese Eat Bats" and "Chinese Are Dirty", respectively. Each data point is normed relative to the maximum search rate. The grey bar represents weeks between January 20, 2020 and March 19, 2020, which represent the first documented positive case in the United States and first state level stay-at-home order issued by California, respectively.

Figure 1b displays Google Search Trends for the terms "Why Chinese Eat Bats" and "Chinese Are Dirty." In the early stages of the pandemic, a prevalent theory suggested that the virus originated from bat consumption in Wuhan's wet markets.[8] Search rates for both terms were relatively low before the first documented U.S. case, then spiked dramatically upon the coronavirus's arrival, before quickly subsiding. This timing suggests that increased interest in Wuhan's wet markets coincided with stronger perceptions of Chinese people as "dirty." Together, Figures 1a and 1b provide *prima facie* evidence that sentiment towards Asians could have shifted negatively in the early days of the pandemic.[9]

Beliefs about virus transmission offer an alternative explanation for changes in patronage to Asian businesses. Consumers may have avoided Asian establishments if they associated them with a higher risk of virus transmission. Such beliefs could have been accurate if Asian businesses were indeed more likely to receive visits from recent travelers to Asia. However, these beliefs might also have been inaccurate if recent travelers to Asia were equally likely to visit non-Asian and Asian businesses. It is important to note that considerable uncertainty surrounded virus transmission in the pandemic's early days, with questions ranging from person-to-person spread to potential transmission via mail packages.[10] Given this context, it is plausible that consumers responded to the virus by attempting to reduce exposure to locations perceived as having greater foot traffic from recent travelers to Asia, potentially viewing Asian restaurants as higher risk in this regard.

Although our research design does not leverage random variation in sentiment or beliefs, it provides suggestive evidence on the mechanisms underlying our results.

2.2 Intragroup Differences

Much of the theoretical and empirical economics research on discrimination focuses on intergroup rather than intragroup differences. However, several compelling empirical studies suggest that intragroup differences also meaningfully affect outcomes. For instance, Kreis-

[8] As noted in this Foreign Policy article, the link between the consumption of bats and the virus gave social media users sufficient fodder for creating memes depicting Chinese as dirty.

[9] Google Search Trends includes search interest by state, but only reports state level search rates that surpass an unobserved minimum threshold. Only 8 states searched "Why Chinese Eat Bats" enough to show data, and of these 8, the top 5 are Georgia, Illinois, New York, California, and Florida. Only 2 states searched "Chinese Are Dirty" enough to show data, and these are California and New York.

[10] See, for example, this CBSnews article titled *No, you won't contract coronavirus from a package you receive in the mail* published on March 5, 2020.

man and Rangel (2015) finds that the widening Black-White wage gap with work experience is driven by the differential between darker-skinned, not lighter-skinned, Black workers and White workers. Similarly, Grogger (2011) reports that Black workers who speak African American Vernacular English earn roughly 12% less than White workers with similar observable skills. These studies indicate that members within a minority group may experience discrimination differently due to variations in attributes such as skin tone and speech patterns. Generally, members of the minority group with features more proximate to the majority group tend to fare better in economic outcomes (de Lafuente (2021)).

For Asians, there is limited economics research on intragroup outcomes, but existing work reveals similar patterns. An audit study conducted before the pandemic by Oreopoulos (2011) demonstrates that concerns over language assimilation led to lower callback rates for South and East Asian immigrants in Canada. In the context of the Covid-19 pandemic, Honoré and Hu (2022) finds that Asian Americans without college degrees experienced particularly large employment declines compared to other racial groups. These results were primarily driven by foreign-born rather than native-born Asian Americans, suggesting that cultural assimilation influenced how Asian workers fared in the labor market during the pandemic.

These studies underscore the importance of cultural assimilation, though defining and measuring the assimilation of a business is challenging and not typically captured in standard data. To address this, we consider a business's geographic location as a potential indicator of assimilation. The concept of restaurant assimilation is relatively familiar: establishments within ethnic enclaves are often perceived as less integrated and more authentic than those outside. Ethnic restaurant enclaves tend to feature attributes such as foreign language signage and decor that are less common in other neighborhoods. While location relative to enclaves may not perfectly capture assimilation, economics research has associated ethnic enclaves with stronger attachments to foreign languages and social ties to recent immigrants (Edin et al. (2003), Damm (2009)). Additionally, sociological studies have used cuisine authenticity as a measure of cultural assimilation (Diaz and Ore (2022)).

2.3 Focal Period

The social and economic policies implemented in March 2020 represent unprecedented structural changes.[11] The pandemic economy was characterized by the Great Resignation, sharp declines in service sector spending, and the work-from-home movement, among other phenomena. Emerging research confirms that the pandemic had racially disparate effects, even though policies and programs were not racially targeted. For instance, foreign-born Asian Americans experienced particularly sharp employment losses (Honoré and Hu (2022)), while Black-owned businesses were least likely to receive Paycheck Protection Program loans from small and mid-sized banks (T Howell et al. (2023)). In the restaurant sector, shifts towards takeout and outdoor dining may have impacted racial groups differently for reasons unrelated to racial attitudes.

Further, recent economics research demonstrates that structural economic changes can significantly impact racial disparities in socioeconomic outcomes, despite being ostensibly race-neutral, due to pre-existing differences among racial groups (Bayer and Charles (2018)). For example, Derenoncourt and Montialoux (2021) shows that the 1966 Fair Labor Standards Act's extension of minimum wage coverage substantially contributed to narrowing the Black-White earnings gap during the civil rights era, due to Black workers' disproportionate representation in previously uncovered economic sectors. Such findings highlight how seemingly neutral policies can have profound effects on racial economic disparities, emphasizing the importance of considering these dynamics in understanding socioeconomic outcomes.

Ideally, research would isolate changes in racial attitudes and/or beliefs while holding other factors constant. In our context, it seems implausible to control for all of the various economic changes in March 2020 that could potentially generate disparate impacts on the demand for non-Asian and Asian cuisine. An approach is to focus on the timeframe preceding major structural economic changes that could confound the analysis, allowing for a more focused examination of shifts in consumer behavior potentially driven by changing racial attitudes. The period between the first documented U.S. case and the first state-level stay-at-home order—our Focal Period—represents the closest approximation to this ideal design. We describe the data next.

[11]The $2.2 trillion Coronavirus Aid, Relief, and Economic Security (CARES) Act was unprecedented in size and scope, more than doubling the $831 billion economic stimulus package passed during the Great Recession.

3 Data and Descriptive Statistics

3.1 Places of Interest (POI) Data

At the time of writing, the SafeGraph POI data contained 622,103 restaurants in the United States.[12] The data categorize restaurants by ethnicity and service type, with an ethnic breakdown of approximately 63% non-ethnic, 13% Asian, 11% Mexican, 6% European, and 5% consisting of other categories.[13] The ethnicity tags are granular, allowing us to distinguish between Vietnamese, Chinese, Korean, Thai, and Japanese restaurants, which is particularly relevant for analyzing changes in consumer behavior towards Asian businesses during the early stages of the Covid-19 pandemic.

Ideally, we would have access to a national restaurant database to construct stylized facts for comparison with SafeGraph's POI data for validation. In the absence of such data, we compare SafeGraph's POI data with facts documented in secondary sources. Panel (a) of Figure 2 plots all Chinese restaurants across the United States using SafeGraph data, while Panel (b) shows a similar map originally published in the Washington Post using Yelp restaurant data.[14] The maps reveal that Chinese restaurants span the entire country but cluster significantly along the east and west coasts, with the highest concentrations in Middle Atlantic (∼20%), Southern Atlantic (∼19%), and Pacific West (∼19%) states.[15] Additionally, clustering occurs within states; for example, nearly three-fourths of New York's Chinese restaurants are located in the New York City metropolitan area.[16] The similarity

[12]This does not include the 198 restaurants that we could not match to a census block group.

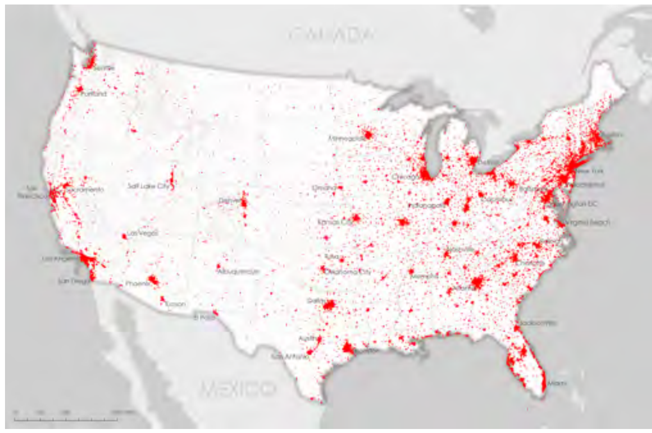
[13]There are 35,579 Chinese restaurants, constituting about 6% of all restaurants and 44% of all East Asian and Southeast Asian restaurants in the dataset. There are also 2,034 Panda Express and 219 P.F. Chang's chains which is comparable to counts we have found online. Approximately 1% of Chinese restaurants are situated within Chinese food enclaves. Non-ethnic restaurants are those under the category tags "American Food", "BBQ and Southern Food", "Burgers", "Chicken Wings", "Fish and Chips", "Fried Chicken", "Hot Dogs", "Pizza", "Healthy Food", "Vegan Food", "Vegetarian Food", "Smoothie and Juice Bar", "Soup", "Salad", and "Fondue". Although fondue originated from Switzerland, we include it in non-ethnic food because there is not a separate "Swiss Food" category tag in the data. Some restaurants serve multiple ethnic cuisines, but fusion restaurants are a small fraction of the total restaurants overall. For example, one is 10 times more likely to encounter a restaurant that is only categorized as Chinese than a restaurant that is tagged as Chinese and another ethnic category. We focus on single ethnicity restaurants.

[14]See the full article here.

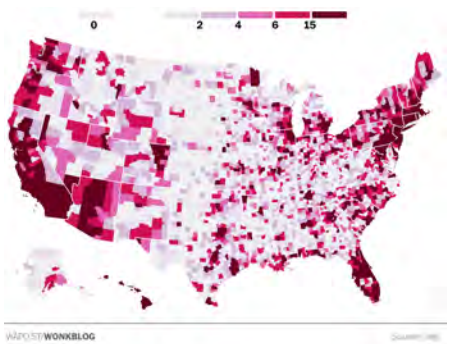
[15]Middle Atlantic states include NY, PA, and NJ; Southern Atlantic states include MD, DC, DE, WV, VA, NC, SC, GA, and FL; and Pacific West states include WA, OR, CA, AK, and HI.

[16]Approximately 73% of New York's Chinese restaurants are in Queens, Kings, New York, Suffolk, Nassau, Bronx, and Westchester counties.

between SafeGraph and Yelp data supports the validity of using SafeGraph's POI data for our analysis.



(a) Distribution of Chinese restaurants using SafeGraph POI data



(b) Distribution of Chinese restaurants listed on Yelp

(c) Word Cloud of Chinese Restaurant Names

Figure 2: Validation of SafeGraph Category Tags

Notes: We use the latitude and longitude coordinates in the Core-POI data files in SafeGraph and map the location of chinese restaurants across the United States using ArcGIS. Restaurants are categorized by ethnicity using SafeGraph's category tags. We use the TagCrowd web application to construct the word cloud to show the most frequently occurring words in Chinese restaurant names. Panel (a) shows that Chinese restaurants in the SafeGraph POI data are dispersed throughout the United States with clusters in large urban centers. Panel (b) shows an analogous map using Chinese restaurants listed on Yelp. Together, panels (a) and (b) show similar patterns with respect to the spatial location of Chinese restaurants across the United States. Panel (c) shows words that are frequently found in Chinese restaurant names using a word cloud.

Another validation exercise involves a simple text analysis of restaurant names, inspired by extensive economics research documenting how personal names can signal ethnic group membership (Bertrand and Mullainathan (2004)). We apply this concept to restaurant names. Panel (c) of Figure 2 presents a word cloud, generated using the TagCrowd web application, displaying the 60 most frequently occurring words across all Chinese restaurant names, excluding the word "restaurant". The word cloud reveals that "china", "chinese", "express", "garden", "golden", "panda", "wok", "buffet", and "dragon" are among the most common words in Chinese restaurant names. These results align with our expectations and corroborate a similar text analysis of Chinese restaurants using Yelp data in the aforementioned Washington Post analysis, further validating the reliability of our SafeGraph dataset.

Table 1: Common Words Found in Restaurant Names Under SafeGraph Category Tags

Chinese Food:	Korean Food:	Thai Food:	Mexican Food:	Italian Food:	American Food:
China	Korean	Thai	Mexican	Pizza	Grill
Chinese	BBQ	Cuisine	Taco	Italian	Bar
Express	Grill	Bangkok	Grill	Pizzeria	House
Garden	House	Asian	Bell	Pasta	Cafe
Panda	Garden	Bistro	El	Grill	Waffle
Buffet	Bonchon	Kitchen	Taqueria	Ristorante	Steakhouse
Wok	Seoul	Sushi	La	Garden	Chili
Golden	Chicken	Cafe	Chipotle	Olive	Wings
Dragon	Sushi	Siam	Box	Cafe	Bistro
House	Tofu	Basil	Burrito	Trattoria	Ihop

Notes: Common words are obtained via the TagCrowd web application that displays word clouds of the 60 most frequently occurring words across all restaurant names for a given ethnic cuisine excluding the word "restaurant". From this set of 60 words, we select 10 that appear to have clouds of the largest size.

Table 1 presents common words found in restaurant names across various ethnic categories, including Korean, Thai, Mexican, Italian, and American cuisine. The prevalent words align intuitively with their respective cuisines. For instance, "Seoul" and "Bonchon" frequently appear in Korean restaurant names, while "Bangkok," "Siam," and "Basil" are common in Thai establishments. Mexican restaurants often include "Taco" and "Taqueria" in their names, and Italian eateries frequently feature "Pizza," "Pizzeria," and "Pasta." These findings demonstrate the granularity of SafeGraph's category tags and provide confidence in the data's ability to distinguish both within Asian ethnic groups (e.g., Korean, Thai) and between broader ethnic categories (e.g., Chinese versus Italian).

3.2 Ethnic Restaurant Enclaves

The SafeGraph data includes latitude and longitude coordinates of all POIs, allowing us to map restaurants to their respective census block groups. Using the ethnicity information for each restaurant, we construct a neighborhood-level measure of ethnic isolation, similar to the isolation index used for residential segregation, as a proxy for identifying ethnic restaurant enclaves. This approach is preferred over using existing lists of ethnic restaurant enclaves from travel guides, as geospatial patterns of racial composition can evolve rapidly, potentially rendering such information obsolete.[17] Additionally, we avoid using residential ethnic enclaves as proxies for restaurant ethnic enclaves, as the correlation between residential and restaurant clusters is imperfect.[18]

To classify neighborhoods as outside or inside an ethnic restaurant enclave, we employ the isolation index, a common measure of residential segregation:

$$I_i^e = \frac{E_i^e}{E^e} \cdot \frac{E_i^e}{T_i} \tag{1}$$

where E^e and E_i^e denote the number of ethnic e restaurants in a metropolitan area and in neighborhood i, respectively, and T_i denotes the total number of restaurants in neighborhood i. Neighborhoods are defined as census block groups and metropolitan areas as core-based statistical areas (CBSA). The index attains higher values when both $\frac{E_i^e}{E^e}$ and $\frac{E_i^e}{T_i}$ are high, indicating that neighborhood i has a larger share of the metropolitan area's ethnicity e restaurants and a large proportion of the neighborhood's restaurants belong to ethnicity e. In the extreme case, if all ethnic e restaurants in a metropolitan area are located in a single neighborhood i, and no other ethnicity is represented there, then $I_i^e = 1$ for i and $I_{i'}^e = 0$ for all other i'. Generally, neighborhoods classified as ethnic e restaurant enclaves will have a larger share of the metropolitan area's ethnic e restaurants and will predominantly feature ethnic e establishments.

We use the index to classify neighborhoods as ethnic food enclaves using the following

[17] For example, in recent decades, the influx of Asian immigrants to Flushing, New York has led to downtown Flushing being commonly referred to as "the Chinese Manhattan": `https://nyti.ms/3aaLjos`. In Chicago, Albany Park, once known as Koreatown in the 70's and 80's, has experienced a significant decline in its Korean population in recent decades: `https://bit.ly/3uI3TgY`.

[18] For instance, while Schaumburg, Naperville, and Skokie, Illinois might be considered Asian Indian residential enclaves due to their relatively high population shares, the most prominent cluster of Indian restaurants is located on Devon Avenue, Chicago.

procedure:

1. For a given ethnicity, e, neighborhoods whose index values exceed the 99th percentile of the neighborhood-level distribution in a given metropolitan area are designated as potential centers of an enclave.

2. From the subset of neighborhoods in Step 1, we remove (i) neighborhoods whose total number of restaurants is less than the average neighborhood (i.e., census block group) in the metropolitan area and (ii) neighborhoods that have fewer than four ethnic e restaurants. Without these two restrictions, we found numerous neighborhoods that were falsely categorized as ethnic enclaves because these neighborhoods had few restaurants total, but all of their restaurants were ethnic e restaurants. This issue was especially problematic in metropolitan areas with relatively few ethnic restaurants total because both terms of the index, $\frac{E_i^e}{E^e}$ and $\frac{E_i^e}{T_i}$, would take high values.

3. Among the resulting subset of neighborhoods, the center of an ethnic restaurant enclave is defined to be the census block group with the maximum value of the index in a given city. This limits a given city to have at most one ethnic e enclave, but allows a metropolitan area to have multiple ethnic e enclaves across different cities.[19]

4. All neighborhoods (i.e., census block groups) whose centroid latitude/longitude coordinates are within 1 mile of the coordinates of the center of the enclave are defined as being part of the ethnic restaurant enclave.

This method enables us to identify and delineate ethnic restaurant enclaves based on the concentration and proportion of ethnic restaurants in specific neighborhoods.

Table 2 shows all U.S. cities classified as having a Chinese restaurant enclave using our procedure. This approach offers several advantages, notably its ability to capture changing demographics over time. For example, in the Los Angeles-Long Beach-Santa Ana area, the rapid growth of the Chinese community in suburban areas has led to Monterey Park being referred to as the first suburban Chinatown, but more recently, the epicenter has shifted to San Gabriel.[20] Our procedure reflects this shift, with San Gabriel, City of Industry, and Monterey Park having the three highest index values in the area, while downtown Los

[19]For example, the city of Boston has only one Chinese restaurant enclave, but the Boston metropolitan area also has another Chinese restaurant enclave in the city of Quincy. The town of Allston is categorized as having a Korean restaurant enclave.

[20]See, for example, this 2014 article from the Los Angeles Times in which a chief executive of a jewelry store in San Gabriel claims that "San Gabriel is famous in China" in reference to its growing popularity as a tourist destination for visitors from China: https://lat.ms/3mxhhRr.

Angeles' Chinatown ranks fourth. This demonstrates the method's ability to capture both broad population shifts and finer changes in Chinese restaurant hubs.

This list includes smaller Chinese restaurant enclaves that are often omitted in popular lists focusing on large urban Chinatowns. For example, in Doraville, GA, our procedure designates census tract 213.01 in DeKalb County as a center of a Chinese restaurant enclave. This aligns with the presence of a significant cluster of Chinese restaurants along Buford Highway.[21] In addition, in Atlanta, census tract 212.04 is also designated as the center of a Chinese restaurant enclave because of a cluster of Chinese restaurants in the Atlanta Chinatown Shopping Mall that is located there. This data-driven approach provides a more comprehensive and up-to-date representation of Chinese restaurant enclaves across the United States.

Table 2: Chinese Restaurant Enclaves Across the United States

Core-Based Statistical Area	**City**	**Isolation Index**
Akron, OH	Aurora	14.353
Atlanta-Sandy Springs-Marietta, GA	Atlanta	15.178
	Doraville	13.354
	Morrow	8.761
	Duluth	8.729
Austin-Round Rock, TX	Manor	4.457
	Austin	3.895
	Cedar Park	3.197
Bethesda-Frederick-Gaithersburg, MD	Rockville	11.802
Boston-Quincy, MA	Boston	22.326
	Quincy	3.815
Cambridge-Newton-Framingham, MA	Everett	12.368
Charlotte-Gastonia-Concord, NC-SC	Charlotte	9.187
Chicago-Naperville-Joliet, IL	Chicago	39.432
Cincinnati-Middletown, OH-KY-IN	Oxford	8.049

Continued on next page

[21]The area is recognized as a hub for authentic Asian cuisine. In the online forum Quora, responses to the question "Is there a Chinatown in Atlanta?" corroborate that our classification matches online sentiment that Buford Highway is a hub for Chinese restaurants. One poster writes, "Atlanta does not have a Chinatown. We have Buford Highway. Buford Highway is a crappy road filled with strip malls, bad architecture, and pavement as far as the eye can see. But it is where to go for Asian food, including Chinese food. There are hole-in-the walls like Ming's Barbecue and larger more elegant spots like Canton Palace. There is Gu's kitchen and many others. But also Korean (though the best Korean has moved further north), Vietnamese, Malaysian, and more. There is some Japanese food, but good Japanese food is also found in Buckhead and elsewhere." The reader can access this forum here.

Table 2 – Chinese Restaurant Enclaves Continued From Previous Page

Core-Based Statistical Area	City	Isolation Index
Cleveland-Elyria-Mentor, OH	Cleveland	18.794
Dallas-Plano-Irving, TX	Plano	16.911
	Richardson	14.155
Denver-Aurora, CO	Aurora	9.960
	Westminster	8.241
Edison, NJ	Highland Park	5.988
	South Plainfield	5.758
	Edison	4.700
Hartford-West Hartford-East Hartford, CT	New Britain	7.406
Honolulu, HI	Honolulu	10.366
Houston-Baytown-Sugar Land, TX	Houston	35.525
	Sugar Land	4.956
	Katy	2.612
Las Vegas-Paradise, NV	Las Vegas	9.623
Los Angeles-Long Beach-Santa Ana, CA	San Gabriel	22.237
	City of Industry	16.326
	Monterey Park	14.352
	Los Angeles	9.716
	Rosemead	8.732
	Alhambra	8.154
	Arcadia	5.214
	Walnut	3.737
	Hacienda Heights	3.618
	Temple City	3.274
Milwaukee-Waukesha-West Allis, WI	West Allis	8.542
Newark-Union, NJ-PA	Dover	6.539
New York-Wayne-White Plains, NY-NJ	New York	34.841
	Flushing	30.269
	Brooklyn	14.071
	Union City	7.832
	Elmhurst	5.677
Oakland-Fremont-Hayward, CA	Oakland	15.650
	Fremont	13.359
	Newark	8.383
	Union City	8.309
	Richmond	6.848
	Pleasanton	5.311
Orlando, FL	Orlando	10.641
Philadelphia, PA	Philadelphia	35.003
Phoenix-Mesa-Scottsdale, AZ	Mesa	20.912
Portland-Vancouver-Beaverton, OR-WA	Portland	13.992
Raleigh-Cary, NC	Raleigh	8.035
Riverside-San Bernardino-Ontario, CA	Rancho Cucamonga	12.812
	Chino Hills	7.862
Sacramento–Arden-Arcade–Roseville, CA	Sacramento	8.502

Continued on next page

Table 2 – Chinese Restaurant Enclaves Continued From Previous Page

Core-Based Statistical Area	City	Isolation Index
St. Louis, MO-IL	Saint Louis	16.982
San Diego-Carlsbad-San Marcos, CA	San Diego	23.211
San Francisco-San Mateo-Redwood City,CA	San Francisco	14.982
	Millbrae	6.262
San Jose-Sunnyvale-Santa Clara, CA	Milpitas	19.369
	San Jose	6.442
	Cupertino	4.073
Santa Ana-Anaheim-Irvine, CA	Irvine	22.396
	Anaheim	5.393
Seattle-Bellevue-Everett, WA	Seattle	23.610
	Bellevue	6.790
	Edmonds	5.104
	Kent	2.779
Washington-Arlington-Alexandria DC-VA	Washington	4.463
Worcester, MA	Worcester	11.449

Note: This list comprises of all core-based statistical areas and cities in which we find a Chinese restaurant enclave. The isolation index is given by: $I_i^e = \frac{E_i^e}{E^e} \cdot \frac{E_i^e}{T_i}$ where E^e and E_i^e denote the number of ethnic e restaurants in a metropolitan area and in neighborhood i, respectively, and T_i denotes the total number of restaurants in neighborhood i.

The index captures variation along the intensive margin whereas conventional lists provide binary classification of ethnic restaurant enclaves. In San Diego, our procedure classifies the "Convoy District" between Aero Drive and Clairemont Mesa Boulevard in the 851.1 census tract as a Chinese restaurant enclave.[22] The area's index value is 23.211, which is comparable to better-known Chinatowns across the country, such as Boston's Chinatown with an index value of 22.326. Without our measure, we might risk mischaracterizing San Diego's Convoy District as a "small" Chinese enclave, when in fact it boasts a diverse and thriving Asian food scene.

This procedure is not specific to Chinese food and can be used to classify other ethnic restaurant enclaves. For example, in the Chicago-Naperville-Joliet metropolitan area, there are clusters of Indian restaurants along Devon Ave, Vietnamese restaurants along Argyle Street (known as "Little Saigon"), Mexican restaurants in Pilsen/South Lawndale, and Greek restaurants on the Near West Side (Greektown). Our procedure correctly categorizes these

[22]This classification is supported by local leisure and hospitality articles that confirm the Convoy district as San Diego's hub for the best Chinese cuisine. For example, see this article.

neighborhoods with their respective ethnic enclaves. Suburban neighborhoods in Glenview and Niles are designated as Korean food enclaves instead of Chicago's Albany Park area, reflecting Korean population flows from the city into the suburbs in recent decades.[23] This approach allows us to examine how foot traffic to Chinese enclaves compares to other ethnic restaurant enclaves.

In the Appendix, we present additional descriptive analyses of ethnic restaurant enclaves, suggesting that neighborhoods classified as food enclaves have a high concentration of co-ethnic restaurants. These analyses also indicate that ethnic food enclaves contain more authentic and less assimilated (i.e., less Americanized) cuisine, as evidenced by the scarcity of large chain restaurants near the enclave centers.

3.3 Estimation Sample

For our main empirical analysis, we use an analysis sample that is subject to two substantive restrictions. The focus is exclusively on full-service restaurants—establishments that provide seated dining with waiter or waitress service and payment after the meal. This focus is motivated by economic theory, which suggests that racial gaps in economic outcomes are shaped by consumers who actively engage with minorities in market settings. We deemed it valuable to concentrate on establishments where prolonged interaction with Asian staff and owners is required. Full-service restaurants account for 77% of all restaurants in the dataset, ensuring that our analysis remains representative of the broader industry.[24]

Second, the primary analysis sample focuses on metropolitan areas with Chinese restaurant enclaves. This decision was motivated, in part, by Honoré and Hu (2022), who found that the pandemic's negative employment effects on Asian Americans were primarily concentrated among foreign-born individuals, suggesting that perceived assimilation played a crucial role. We aimed to explore potential interactions related to the perceived authenticity

[23]For example, this article describes the transition of Chicago's Koreatown, "Korean Americans' exodus from Chicago has had a visible impact on the city, particularly on Lawrence Avenue, a street given the honorary title of 'Seoul Drive.' From 1997 to 2017, the number of Korean businesses on Lawrence fell from 158 to 50."

[24]We have conducted the analysis using only limited-service restaurants. These results do not qualitatively alter our main conclusions. While we observe some evidence of a greater decline in foot traffic to non-Asian limited-service restaurants within enclaves compared to those outside enclaves, and a more pronounced decline in Asian versus non-Asian limited-service restaurants outside of enclaves, these differences are effectively uninformative due to their lack of precision.

of these businesses, and enclaves provided an opportunity to do so. However, analysis based on data for the entire United States are also provided in the Appendix.

The estimation sample consists of a smaller subset of 171,350 restaurants located across 37 metropolitan areas. The total number of observations is 2,194,932, slightly less than 2,227,550 (171,350 restaurants × 13 weeks) due to the sample being an unbalanced panel.[25]

4 Empirical Methodology

To quantify changes in foot traffic to Asian restaurants, both outside Chinese restaurant enclaves and inside enclaves in the pandemic's early months, we employ the following triple difference-in-difference model:

$$y_{it} = \gamma_t + \gamma_t \times Asian_i + \sum_{k=2}^{4} \gamma_t \times D_i^k + \sum_{k=2}^{4} \gamma_t \times D_i^k \times Asian_i + \alpha_i + \epsilon_{it} \quad (2)$$

where y_{it} represents visits to restaurant i at time t, and γ_t denotes time fixed effects. Time is measured in weekly increments from January 5-12 to March 29-April 5, with January 5-12 as the baseline. D_i^k indicates whether restaurant i is within a 1-mile radius of an ethnic restaurant enclave. The k superscript groups enclaves by isolation index, with k indexing four location categories: (i) outside a Chinese restaurant enclave, (ii) inside a low-isolation enclave, (iii) inside a medium-isolation enclave, and (iv) inside a high-isolation enclave.[26] Non-Asian restaurants outside Chinese restaurant enclaves serve as the base group.

$Asian_i$ is an indicator for whether restaurant i is categorized as East Asian or Southeast Asian.[27] This specification is motivated by the possibility that other East Asian cuisines

[25] In the Appendix, we demonstrate that the results are qualitatively similar when restricting the sample to a balanced panel. We constructed a dataset with the widest possible window that would run efficiently on our available computing resources. The size of the data posed computational challenges, limiting our ability to extend the window beyond the current dataset.

[26] Low, medium, and high isolation are defined by neighborhood isolation index values of $<$10, 10-20, and $\geq$20, respectively.

[27] $Asian_i$ includes Korean, Japanese, Vietnamese, Chinese, Thai, Filipino, Indonesian, Mongolian, Hawaiian, and Burmese cuisines because they are relatively proximate to East Asian and Southeast Asian cuisine in terms of the spices and ingredients used. Burmese cuisine is perhaps the most distinct, but our results are not sensitive to including Burmese restaurants due to their relative scarcity in the United States.

besides Chinese could have been impacted by the coronavirus. Spillover effects of this kind have been documented in other contexts; for instance, the Stop AAPI Hate National Report reports that 41.2% of hate crime victims from March 19, 2020, to December 31, 2021, identified as Korean, Filipinx, Japanese, or Vietnamese. In later analyses, we estimate a version of model (2) separately by ethnic cuisine.

The α_i represents a set of restaurant fixed effects, and ϵ_{ijt} is the error term. While our results are not sensitive to the inclusion of restaurant fixed effects, we prefer the model that incorporates them as they account for time-invariant restaurant characteristics during the early months of the pandemic. We compute robust standard errors clustered at the core-based statistical area level.

The estimates inform several key parameters of interest: the change in visits to non-Asian restaurants outside of enclaves (captured by the γ_t parameters), to Asian restaurants outside of Chinese restaurant enclaves (given by the sum of γ_t and $\gamma_t \times Asian_i$), to non-Asian restaurants inside high-isolation Chinese restaurant enclaves (the sum of γ_t and $\gamma_t \times D_i^k$), and to Asian restaurants inside Chinese restaurant enclaves (the sum of γ_t, $\gamma_t \times Asian_i$, $\gamma_t \times D_i^k$, and $\gamma_t \times D_i^k \times Asian_i$). Additionally, we estimate the Asian vs. non-Asian difference in changes in visits either outside of enclaves ($\gamma_t \times Asian_i$) or inside enclaves (the sum of $\gamma_t \times Asian_i$ and $\gamma_t \times D_i^k \times Asian_i$). Finally, the difference in the Asian vs. non-Asian change in visits between outside and inside enclaves is captured by $\gamma_t \times D_i^k \times Asian_i$.

Under the null hypothesis that dining choices were motivated by concerns other than race, we would expect similar foot traffic dynamics for non-Asian and Asian restaurants both outside and inside Chinese enclaves. Specifically, outside enclaves, we would expect $\gamma_t \approx \gamma_t + \gamma_t \times Asian_i$, and inside enclaves, $\gamma_t \times D_i^k \approx \gamma_t \times D_i^k + \gamma_t \times D_i^k \times Asian_i$. In other words, the interactions $\gamma_t \times Asian_i$ and $\gamma_t \times D_i^k \times Asian_i$ should be jointly 0, signaling that changes in foot traffic were not specific to Asian cuisine but broad-based in nature. This would suggest that consumers may have opted to forgo dining out in general to reduce potential virus exposure, rather than specifically avoiding Asian restaurants due to racial concerns.

The alternative hypothesis is that the demand response was specific to Asian cuisine. Foot traffic to Asian restaurants could have declined more than foot traffic to non-Asian restaurants both outside and inside Chinese enclaves (i.e., $\gamma_t \times Asian_i < 0$ and $\gamma_t \times D_i^k \times Asian_i < 0$), or alternatively, it may have declined more than non-Asian restaurants only inside Chinese enclaves but not outside (i.e., $\gamma_t \times Asian_i \approx 0$ and $\gamma_t \times D_i^k \times Asian_i < 0$), indicating disparate impacts *within* Asian restaurants. Another possibility is that consumers substituted away from Asian cuisine toward non-Asian cuisine rather than simply dining at home. For example, $\gamma_t > 0$ and $\gamma_t + \gamma_t \times Asian_i < 0$ would signal an increase in visits to non-Asian restaurants and a corresponding decrease in visits to Asian restaurants outside Chinese enclaves.

In tables, we summarize the dynamics in three time periods: (i) the two weeks prior to the first confirmed coronavirus case in the United States (pre-period), (ii) the seven weeks between the first confirmed case and the first state-level stay-at-home order (focal period), and (iii) the three weeks after the first state-level stay-at-home order (post-stay-at-home period). To translate changes in visits into percent changes, we first estimate the number of visits that would have occurred in each period absent the pandemic. We use the average visits to restaurants in an ethnicity-enclave bin during the baseline week as a measure of potential weekly visits. This baseline estimate is then multiplied by the number of weeks in each period to calculate the total potential visits to the average restaurant in an ethnicity-enclave bin.

5 Empirical Results

5.1 Main Results

Figure 3 illustrates the week-to-week dynamics in visits to Asian and non-Asian restaurants, pooled across both outside and inside high-isolation Chinese restaurant enclaves, during the early stages of the pandemic. For brevity, we focus on results for high-isolation Chinese enclaves, as foot traffic patterns in low and medium isolation enclaves are similar to those outside enclaves.[28] The unshaded region in the plots indicates our focal period of analysis. The first shaded region represents weeks prior to the first laboratory-confirmed coronavirus case in the United States, while the second shaded region shows weeks following the first state-imposed stay-at-home order.

Panel (3a) demonstrates that visits to both Asian and non-Asian restaurants remained

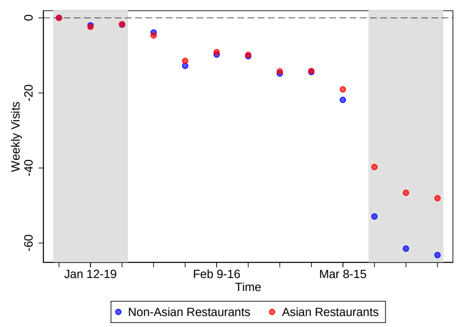
[28] Results for low- and medium-isolation enclaves, along with specifications pooling all enclave types, are presented in the Appendix.

stable in late January, suggesting consumer attitudes were consistent prior to the first confirmed U.S. coronavirus case. Both restaurant types then experienced a notable decline in visits during February. Importantly, during the focal period, the differences between the two time series are negligible, contradicting the early narrative that the decline in foot traffic to Asian restaurants was race-specific. Similar figures in the Appendix confirm that foot traffic to both Chinese and non-Chinese restaurants declined during the focal period, with no significant difference in their rates of change.

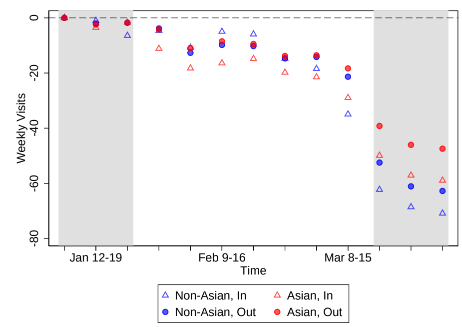
In the Post-Stay-at-Home period, visits decline precipitously, with a greater decrease for non-Asian than Asian restaurants. However, we do not interpret this as evidence of improved consumer sentiment towards Asians. We consider the Post-Stay-at-Home period to be less informative about changes in consumers' racial sentiment, as unprecedented economic shocks may have interacted differently with Asian restaurants and Asian restaurant enclaves for reasons unrelated to race.

Panel (3b) reveals distinct patterns for restaurants within versus outside these enclaves. Time series begin to diverge in early February 2020, with Asian restaurants in high-isolation Chinese enclaves experiencing the largest decline in foot traffic compared to other groups (non-Asian outside enclaves, non-Asian inside enclaves, and Asian outside enclaves), a trend that persists until stay-at-home orders were imposed. In mid-February, non-Asian restaurants within Chinese enclaves outperformed other groups for two consecutive weeks, experiencing the smallest declines in foot traffic.

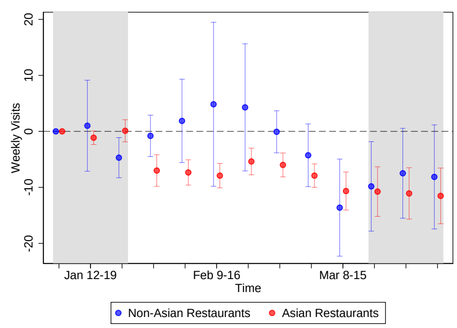
Figure 3: Week-to-Week Foot Traffic in the Early Days of the Pandemic



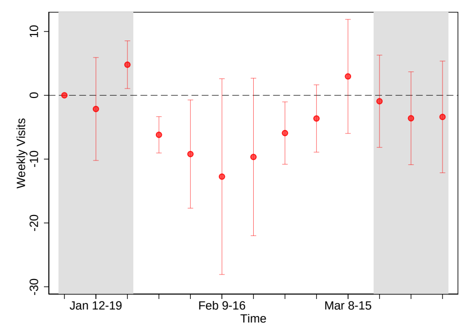
(a) Visits by Ethnicity



(b) Visits by Ethnicity and by Enclave



(c) In vs Out Difference, by Ethnicity



(d) Asian vs Non-Asian, In vs Out

Notes: These estimates and 95% confidence intervals are obtained from our baseline regression with standard errors clustered at the core-based statistical area level. We plot foot traffic patterns for non-Asian and Asian restaurants outside and inside high-isolation Chinese food enclaves. The clear region is the focal period of our analysis. The first shaded block indicates weeks prior to the first laboratory-confirmed coronavirus case in the United States, and the second shaded block represents weeks after the first state level stay-at-home order in the United States.

Panel (3c) clearly shows that Asian restaurants in enclaves experienced greater declines in visits compared to their counterparts outside enclaves. Conversely, non-Asian restaurants inside Chinese food enclaves began to experience a relative increase in foot traffic around the same time Asian restaurants inside enclaves started their relative decline. This pattern suggests a potential substitution away from Asian restaurants towards non-Asian restaurants within ethnic enclaves in early to mid-February. However, the overlapping confidence intervals indicate that we cannot reject the null hypothesis that the in-versus-out differences in foot traffic changes are statistically indistinguishable between non-Asian and Asian restaurants.

Panel (3d) indicates that Asian restaurants in Chinese enclaves began experiencing a relative decline in visits during the last week of January, specifically the week of January 26 to February 1. This coincides with the January 31 announcement of the first confirmed coronavirus case in the United States, suggesting this event marked a pivotal moment in the pandemic's early impact. The relative decline in foot traffic intensified over the next two weeks, reaching its lowest point during the week of February 9 to 16. From that point onward, the decline began to reverse, with the difference converging toward zero and stabilizing after the week of March 8 to 15. Importantly, the closing of the gap between Asian and non-Asian restaurants inside versus outside enclaves was driven by a sharp decline in visits to non-Asian restaurants within enclaves, rather than a recovery in foot traffic for Asian restaurants inside enclaves.

Table 4 quantifies the total changes observed in the preceding figures. The first three rows show changes in visits to non-Asian restaurants, while the next three rows show the difference in these changes between Asian and non-Asian restaurants. The total change for Asian restaurants is the sum of the main and interaction effects. Columns (1), (2), and (3) present these changes for all restaurants, those outside high-isolation Chinese restaurant enclaves, and those inside, respectively. Column (4) shows the difference in visit changes across locations. Columns (5) to (8) translate these changes into percentages by dividing by the total expected visits to restaurants in each ethnicity-enclave bin, based on baseline week visits.

The first three rows of column (1) reveal that visits to non-Asian restaurants declined by approximately 4, 88, and 178 visits in the Pre-Period, Focal Period, and Post-Stay-at-Home Period, respectively, corresponding to declines of 2%, 15%, and 71%. The 15% decline in visits to non-Asian restaurants during the focal period indicates that Asian restaurants were *not* alone in experiencing reduced foot traffic prior to the implementation of stay-at-home orders.

The next three rows illustrate differences in foot traffic changes between Asian and non-Asian restaurants. The magnitudes of the Pre-Period $\times$ Asian interaction are small, suggesting that foot traffic to Asian restaurants was indistinguishable from that of non-Asian restaurants in the pre-period. Standard Wald tests for this interaction yield p-values of 0.691, 0.574, 0.676, and 0.624 for all restaurants, restaurants outside enclaves, inside enclaves, and the In-Out difference, respectively. These results confirm parallel pre-trends during the three weeks preceding the Focal Period.

In columns (1) to (3), the Post-Stay-at-Home × Asian interaction, however, is positive and statistically significant, suggesting Asian restaurants experienced a less severe decline than non-Asian restaurants after stay-at-home orders were imposed. We do not interpret this as evidence of increased positive sentiment towards Asian businesses, as Covid-19 policies exerted unprecedented macroeconomic pressures that could have had disparate impacts on different economic subgroups, including Asians.

Table 3: Visits to Asian and Non-Asian Restaurants In and Out of Chinese Food Enclaves

Dep Var: Visits								
	Δ in levels				Δ in % terms			
	All	Out	In	In-Out	All	Out	In	In-Out
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pre-Period	-3.801	-3.784	-7.472	-3.687	-0.023	-0.023	-0.043	-0.021
	(1.003)	(0.966)	(5.476)	(5.404)	(0.006)	(0.006)	(0.032)	(0.031)
Focal Period	-87.759	-86.716	-94.489	-7.773	-0.150	-0.148	-0.157	-0.013
	(4.951)	(4.992)	(16.087)	(15.384)	(0.008)	(0.009)	(0.027)	(0.026)
Post-Stay-at-Home	-177.584	-176.322	-201.756	-25.434	-0.706	-0.703	-0.781	-0.098
	(8.168)	(8.552)	(6.870)	(11.911)	(0.032)	(0.034)	(0.027)	(0.046)
Pre-Period × Asian	-0.290	-0.396	2.256	2.652	-0.002	-0.003	0.016	0.019
	(0.725)	(0.698)	(5.350)	(5.364)	(0.006)	(0.005)	(0.037)	(0.037)
Focal Period × Asian	5.159	7.973	-36.412	-44.386	0.011	0.017	-0.073	-0.088
	(3.438)	(3.499)	(16.629)	(16.283)	(0.008)	(0.008)	(0.033)	(0.032)
Post-Stay-at-Home × Asian	43.213	43.666	35.749	-7.917	0.220	0.223	0.166	-0.037
	(4.857)	(4.794)	(10.091)	(10.961)	(0.025)	(0.025)	(0.047)	(0.051)

Notes: The baseline period is the week of January 5 to 12. The sample includes restaurants in the 37 core-based statistical areas that have a Chinese restaurant enclave. In this set of results, Chinese restaurant enclaves are restaurants within a 1 mile radius of the neighborhood with the maximum value of the isolation index among all neighborhoods in the city and the maximum value exceeds 20. Columns (5) to (8) show results as a percent of the total expected visits based on the average visits to non-Asian restaurants in the baseline week. The total expected visits is adjusted to match the number of weeks in the remaining time in January, all of February, and all of March. Standard errors are clustered at the core-based statistical area level.

The next two columns separate results for restaurants outside and inside high-isolation Chinese food enclaves. Estimates for restaurants outside enclaves (columns (2) and (6)) mirror those for all restaurants (columns (1) and (5)). Outside Chinese restaurant enclaves, the decline in visits to Asian restaurants was about 8 visits less than for non-Asian restaurants during the focal period. However, a different pattern emerges for restaurants inside Chinese food enclaves, particularly during the focal period. The Focal Period × Asian interaction shows that the average Asian restaurant in high-isolation Chinese restaurant enclaves lost approximately 36 more visits compared to the average non-Asian restaurant in enclaves, and nearly 130 visits in total. This interaction estimate is statistically significant at the 5% level (p-value = 0.035). In percentage terms, foot traffic to Asian restaurants in enclaves fell by roughly 23%, which is 7.3 percentage points larger than the 15.7% decline for non-Asian restaurants in enclaves. Consequently, within enclaves, Asian restaurants experienced nearly 45% more lost visits than non-Asian restaurants.

Columns (4) and (8) present the triple-difference estimates in levels and percentage terms, respectively. During the focal period, the gap between Asian and non-Asian restaurants widened by 44 visits, or 8.8 percentage points more inside versus outside enclaves. This estimate is statistically significant at the 1% level. In contrast, the triple-difference estimates for the pre-period and post-stay-at-home period are close to zero and not statistically significant at any conventional levels.

An important consideration is whether ethnic food enclaves primarily serve co-ethnic patrons, in which case declines in foot traffic could potentially be driven by Asian consumers. Using the 5-year 2016-2020 American Community Survey (ACS), we calculate the proportion of Asian residents living in census block groups within a 1-mile radius of the enclave center and observe significant variation in the ethnic composition surrounding high-isolation Chinese restaurant enclaves. For example, Chinese food enclaves in San Gabriel, CA, Flushing, NY, and Rosemead, CA, have supermajority Asian populations within a 1-mile radius of 73.8%, 71%, and 67% Asian, respectively. In contrast, all other high-isolation restaurant enclaves have less than 50% Asian residents in their vicinity.

In the Appendix, we show that the declines in foot traffic to Chinese food enclaves are comparable across areas with differing residential Asian shares. While proximity does not guarantee patronage, economic research on restaurant demand provides strong evidence that travel time significantly influences consumer choice (Athey et al. (2018)). Given this context, it is plausible that market participants in high Asian share enclaves might be disproportionately Asian, given the high residential Asian shares and the critical role of distance in determining restaurant choice. However, this suggests that co-ethnic patrons are not necessarily driving our results.

To summarize, our findings reveal that both Asian and non-Asian restaurants experienced comparable declines in foot traffic, approximately 15%, during the pandemic's early stages. However, Asian restaurants in high-isolation Chinese enclaves faced a more pronounced decrease in foot traffic compared to Asian restaurants outside these enclaves and non-Asian restaurants. As detailed in the Appendix, this pattern does not appear to be driven by co-ethnic patrons, labor supply adjustments, or shifts in operations.[29] We next explore an alternative explanation: consumers may have sought to avoid restaurant enclaves in general, as enclaves across all ethnic groups might share attributes that consumers found less desirable given the virus-related health risks.

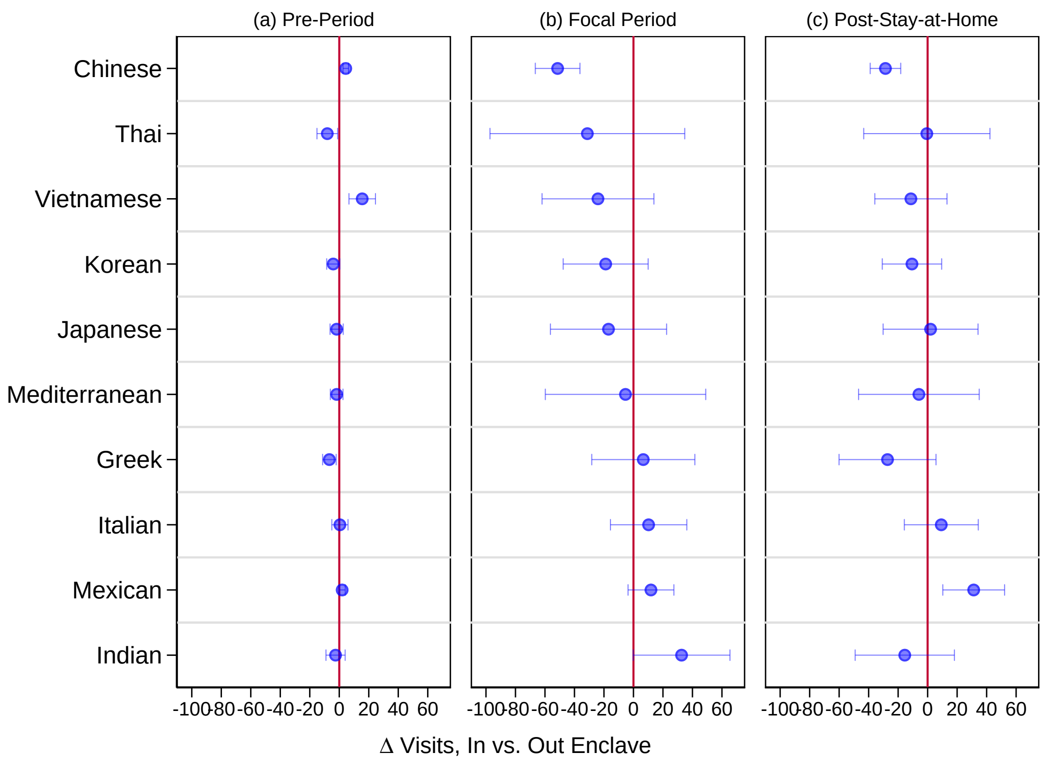
5.2 Enclave Effects by Ethnicity

Consumers may have sought to avoid not only "Chinatowns" but also "Greektowns," "Koreatowns," "Little Italys," and other ethnic restaurant enclaves during the focal period. If ethnic restaurant enclaves shared characteristics that interacted with the arrival of the coronavirus in a way that reduced consumer demand, the differential decline in foot traffic to restaurant enclaves would not be unique to Chinese enclaves. To examine this, we identify restaurant enclaves for different ethnic groups using the same procedure applied to Chinese restaurant enclaves. For each ethnicity, we estimate the difference in changes in visits to ethnic restaurants located inside versus outside of their respective enclaves during the Pre-Period, Focal Period, and Post-Stay-at-Home Period. To improve precision, we pool low, medium, and high isolation enclaves, but the results remain qualitatively similar regardless of whether the enclaves are pooled or analyzed separately.

Figure 4 illustrates the difference in visit changes during the Pre-Period, Focal Period, and Post-Stay-at-Home Period for restaurants inside versus outside enclaves. Panel (a) demonstrates that in the Pre-Period, these differences are generally centered around zero, indicating that changes in foot traffic were similar inside and outside enclaves across various ethnic cuisines before the arrival of Covid-19.

[29] In the Appendix, we present supplementary analyses that address potential alternative explanations for our findings. These analyses demonstrate that our results are unlikely to be attributed to Asian restaurants within enclaves adapting their operations (e.g., switching to take-out-only service) or closing earlier than other restaurant types. Furthermore, we provide evidence that does not support the hypothesis that our main results are primarily driven by labor supply issues rather than shifts in consumer demand.

Figure 4: In vs Out Enclave Changes in Visits by Ethnicity



Notes: We run a regression of weekly visits on a set of time fixed effects, time fixed effects interacted with an indicator for whether the restaurant is located inside an ethnic restaurant enclave, and restaurant fixed effects separately for each ethnicity. We aggregate the time-by-enclave interaction terms to obtain how the change in foot traffic differs for restaurants inside versus outside their respective ethnic enclaves. These difference-in-difference estimates are plotted above separately by ethnicity and month.

Panel (b) reveals a distinct pattern during the focal period. Chinese restaurants inside enclaves experienced an average of 51 fewer visits compared to those outside enclaves. The 95% confidence interval excludes zero, indicating statistical significance at conventional levels. Thai, Vietnamese, Korean, and Japanese restaurants follow as the next four ethnic cuisines experiencing sharper declines in foot traffic inside versus outside enclaves. Although the in-versus-out differences for these ethnic groups are not statistically significant, it is noteworthy that the five ethnic cuisines whose enclaves experienced the most pronounced relative declines in restaurant foot traffic are all East Asian.

In contrast, the differences in foot traffic to Mediterranean, Greek, Mexican, Italian, and Indian restaurants inside versus outside their respective enclaves during the focal period are either close to zero or positive. This suggests that restaurants inside these ethnic enclaves actually experienced smaller declines compared to their counterparts outside enclaves. While none of these estimates are statistically significant at the conventional 5% level, the point estimates indicate that the negative enclave effect is not shared by these non-East Asian cuisines.

Unlike the Focal Period, the Post-Stay-at-Home Period shows no clear ethnic ordering in the differences in foot traffic between restaurants inside versus outside enclaves. Greek restaurants inside Greek restaurant enclaves experience a 10.5 percentage point steeper decline in foot traffic compared to those outside enclaves. Similarly, Indian restaurants inside enclaves show a 7.7 percentage point greater decline than those outside. In contrast, Thai and Japanese restaurants exhibit essentially no difference in foot traffic between those inside and outside their respective enclaves.

One possible explanation for these results, beyond an increase in negative sentiment towards Asians, could be related to the earlier detection of coronavirus cases in East Asian countries. Thailand reported the first positive case outside of China on January 13, 2020, with Japan and Korea following within a week. During the focal period, there was significant uncertainty regarding coronavirus transmission. In the absence of clear scientific information, consumers may have relied more on heuristics to guide their decision-making. One such heuristic could have been the presence of documented coronavirus cases in other countries.

Italy offers an intriguing comparison in this context. As a Western European country, Italy's first confirmed coronavirus case was also reported during the focal period, on February 21, 2020. Shortly after, cases in the United States were linked to travel to and from Italy. Italian restaurants are also known for their enclaves, often referred to as "Little Italys." In the following section, we re-index time and conduct event studies to examine whether Italian restaurant enclaves experienced sharp declines in foot traffic after Italy's first positive case or after cases in the United States were linked to travel from Italy.

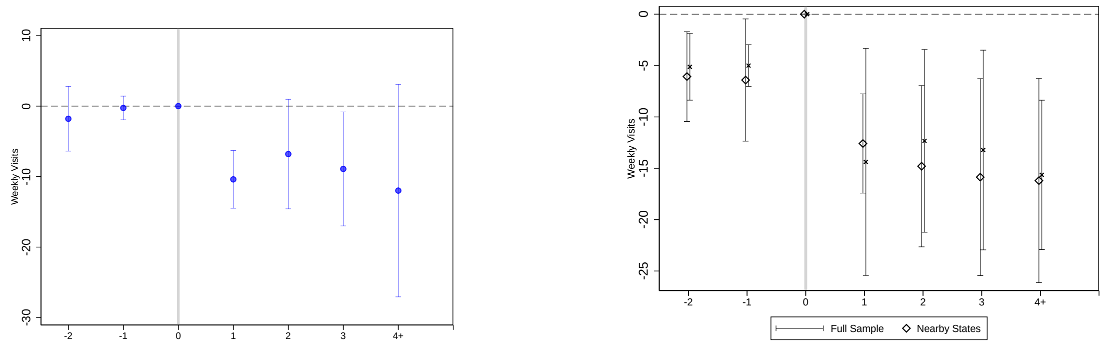
5.3 Event Study Analysis: Italian Restaurant Enclaves

We restrict our sample to Chinese and Italian restaurants and conduct an event-study style analysis, re-indexing time relative to events associated with cross-country virus transmission. In the early days of the pandemic, we consider two types of events as potential catalysts for decreased demand for dining in ethnic enclaves: announcements of confirmed positive cases in other countries and announcements that U.S. cases were due to travel from another country. These announcements could have dampened demand for various reasons; for example, learning that the coronavirus was circulating in Italy or that U.S. cases were linked to travel from Italy might have made consumers wary of visiting Italian restaurant enclaves.

Figures 5a and 5b present event-study estimates, with time redefined relative to specific events. For Chinese restaurants, the "0" period corresponds to the week of the first confirmed U.S. case in both panels. For Italian restaurants, the "0" period in Figure 5a corresponds to the week of Italy's first confirmed case, while in Figure 5b, it corresponds to the week of the first U.S. case linked to recent travel from Italy. It is worth noting that these announcements occurred four and two weeks, respectively, before the first state-level lockdown in the U.S. Consequently, in Figures 5a and 5b, the 4+ period and the 2 to 4+ periods for Italian restaurants fall within the post-lockdown timeline. Given that pandemic lockdowns coincided with significant macroeconomic disruptions, greater emphasis is placed on the 1 to 3 periods in Figure 5a and the 1 period in Figure 5b. Additionally, in Figure 5b, we provide results limited to data from states relatively close to Rhode Island, where the first U.S. coronavirus case tied to travel from Italy was reported.[30] This adjustment considers the possibility that news related to the case may have been more salient in markets geographically proximate to Rhode Island.

[30]The states included are Rhode Island, Connecticut, Massachusetts, New Jersey, New York, and Pennsylvania.

Figure 5: Week-to-Week Foot Traffic: Chinatown and Little Italy



(a) Visits by Ethnicity and by Enclave

(b) In vs Out Difference, by Ethnicity

Notes: In Panel (5a), the event is defined as the week in which the first coronavirus case was announced in the United States for Chinese restaurants, and the week in which the first coronavirus case was announced in Italy for Italian restaurants. In Panel (5b), the event is defined as the week in which the first coronavirus case was announced in the United States for Chinese restaurants, and the week in which the first coronavirus case in the United States due to travel to Italy was announced for Italian restaurants. Standard errors are clustered at the core-based statistical area.

In Figure 5a, the estimates reveal that in the week following the announcement of coronavirus circulation in Italy, visits to Chinese restaurant enclaves declined by approximately 10 visits more than to Italian restaurant enclaves (according to the triple difference), and remained at this lower level thereafter.

Figure 5b presents event-study estimates relative to the week of the first documented U.S. case due to recent travel to China and Italy, respectively. Two time series are shown: one using the pooled sample of all Chinese and Italian restaurants, and another using only states in closer proximity to Rhode Island. If consumers responded similarly to news of U.S. cases linked to travel from Italy as they did to cases linked to China, we would expect the time series to be near zero in the week following the news. The coefficients for the two periods prior to the event suggest that visits to Chinese restaurants in enclaves were already in relative decline before the arrival of cases from Italy, which aligns with our main results and the sequence of announcements. However, in the subsequent week, there is no evidence that Italian restaurants in enclaves, either nationwide or in nearby states, experienced a relative decline in visits of similar magnitude to their Chinese counterparts.

Overall, these results indicate that Italian restaurants in Italian enclaves did not experience the same demand decline as Chinese restaurants following news of positive cases linked to recent travel from Italy and China, respectively. It is unlikely that this pattern can be attributed to consumers becoming desensitized to coronavirus news by the time cases linked to travel from Italy were confirmed in the United States. The implementation of broad shelter-in-place lockdowns shortly after the arrival of cases from Italy suggests that concerns about virus transmission were escalating rather than moderating during this period. Another possible explanation, aside from negative racial sentiment, could be that consumers were responding to perceived differences in transmission risk between Italian and Chinese restaurant enclaves. We will examine this possibility next.

6 Potential Mechanisms

Our findings reveal that Asian restaurants in high-isolation Chinese enclaves experienced more pronounced decreases in foot traffic compared to Asian restaurants outside these enclaves and non-Asian restaurants. This pattern does not appear to be driven by a general desire to avoid ethnic enclaves (as shown above), co-ethnic patronage, labor supply adjustments, or shifts in operations (as detailed in the Appendix). In this section, we examine two additional potential explanations for this disparity: (1) consumers may have perceived a higher transmission risk in Chinese enclaves, possibly due to visits from recent travelers to China, or (2) the pandemic may have activated negative sentiment towards Chinese businesses, particularly those perceived as more foreign and less assimilated.

Given that international travel was a primary driver of cross-country virus transmission, consumers in areas with large inflows of recent travelers from China may have had a rational basis for exercising caution. While data limitations prevent us from directly measuring the share of visits by recent China travelers to Chinese enclaves, we can construct a measure of exposure to international travelers using SafeGraph data on cell phones' country of origin.[31] This variable allows us to calculate the share of restaurant visits from individuals who recently spent significant time outside the United States. Although we cannot specifically measure visits by recent China visitors, we can assess the share of foot traffic to ethnic restau-

[31] Country of origin is determined by the cell phone's nighttime location (between 6pm and 7am) over a 6-week period. SafeGraph requires a "sufficient amount of evidence (total data points and distinct days)" to assign a home for the device.

rants inside enclaves from international visitors, providing insight into potential transmission risk perceptions.

To investigate the role of anti-Asian sentiment, we analyze metropolitan area-level variation in Google search intensity for the term "Kung Flu". While other terms like "Chinese Virus" or "Wuhan Virus" have also been criticized as inflammatory, "Kung Flu" is particularly problematic as it relies on an ethnic stereotype associating martial arts with Chinese culture, making it harder to justify as merely conveying geographic origins. The viral spread of social media memes incorporating martial arts tropes during the early months of the pandemic further illustrates how "Kung Flu" could be characterized as antilocution—casual negative remarks often made in jest—which Allport's seminal work "The Nature of Prejudice" identifies as an early form of social prejudice. This analysis enables us to explore potential links between such rhetoric and changes in consumer behavior towards Chinese restaurants.

Table 4 presents regression estimates of lost visits to Chinese enclaves during the focal period on various metropolitan area-level predictors. Columns (1) and (2) show that Chinese restaurant enclaves in metropolitan areas with "Kung Flu" Search Intensity one standard deviation above the mean experienced a decline in foot traffic 6.6 to 7.7 percentage points greater than those in average metropolitan areas during the Focal Period. These estimates are statistically significant at conventional levels. The difference between the first two columns is that column (1) excludes six metropolitan areas whose estimates are more extreme and less precise due to smaller sample size.[32] These findings suggest a potential link between the prevalence of politically charged rhetoric and consumer behavior towards Chinese restaurants.

In column (3), we replace Kung Flu" Search Intensity with a measure of Racially Charged Search, based on Google search intensity for the n-word during the analysis period—an alternative measure of racial sentiment used in prior research to study racial bias in voter choice Stephens-Davidowitz (2012). The estimate suggests that Chinese restaurant enclaves

[32]These areas have relatively small sample sizes, and consequently, their estimates of the Focal Period declines are less precise and tend to be more extreme. In the metropolitan area level analysis, these MSAs contribute minimally to the estimates and do not significantly impact the results, whether included or excluded, due to their Google Search Trends being close to the mean. In the primary analysis, our results also remain robust regardless of their inclusion or exclusion due to their aforementioned relatively small number of observations.

in metropolitan areas with higher Racially Charged Search experienced a less severe decline in visits, averaging roughly 3.6 percentage points during the Focal Period, though this estimate is not statistically significant. In column (4), we include both measures of racial attitudes, finding that only Kung Flu" Search Intensity is predictive of metropolitan area-level declines in foot traffic to Chinese enclaves. This suggests that specific anti-Asian sentiment, rather than general racial bias, better explains the decline in traffic to Asian restaurants within enclaves at the metropolitan level.

Table 4: Predictors of Focal Period Enclave Effects at Metropolitan Area Level

Dep Var: Focal Period Chinese Enclave Effects								
Antilocution	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Search Intensity for "Kung Flu" (in sd)	-0.077	-0.066		-0.067	-0.064	-0.071	-0.062	-0.001
	(0.021)	(0.031)		(0.042)	(0.047)	(0.052)	(0.054)	(0.057)
Racially Charged Search			0.036	-0.002	-0.005	-0.002	-0.007	0.007
			(0.028)	(0.036)	(0.042)	(0.044)	(0.045)	(0.042)
Demographic Controls								
Asian Dissimilarity Index					0.001	0.001	0.002	0.001
					(0.004)	(0.004)	(0.004)	(0.004)
Share of Asian Population						0.001	0.001	0.003
						(0.003)	(0.003)	(0.003)
International Travel								
% Int'l Visits in Asian Restaurants in Enclaves							-0.005	0.003
							(0.007)	(0.008)
Partisanship								
2016 Trump Vote Share								0.005
								(0.002)
Observations	31	37	37	37	37	37	37	37
R-squared	0.310	0.112	0.044	0.112	0.113	0.117	0.131	0.263

Notes: The dependent variable is the difference in the change in visits to Asian versus non-Asian restaurants inside versus outside of enclaves during the Focal Period at the metropolitan area level. Each regression is weighted by the precision of the estimated relative decline in the Focal Period.

In columns (5) and (6), we introduce controls for the metropolitan area-level Asian Dissimilarity Index, a standard measure of residential segregation, and the Share of Asian Population. These specifications are motivated by literature suggesting inter-ethnic contact is an important determinant of attitudes towards others (Bursztyn et al. (2024), Rao (2019), Corno et al. (2022), Boisjoly et al. (2006)). The point estimate for "Kung Flu" Search Intensity remains stable but becomes less precise and statistically insignificant, indicating that demographic controls explain some metropolitan area-level variation in "Kung Flu" search intensity. The near-zero coefficients for demographic controls suggest that, conditional on our measure of antilocution, greater Asian integration and population share are not predictive of observed enclave effects.

In column (7), we compare our measure of antilocution against exposure to international travelers in Chinese enclaves. The estimate for Kung Flu" Search Intensity remains stable, indicating a meaningful relationship with lost visits, while the measure of exposure to international travelers shows no significant effect. Specifically, Chinese restaurant enclaves in metropolitan areas one standard deviation above the mean Kung Flu" Search Intensity are expected to experience a 6.2 percentage point greater decline in foot traffic compared to the average during the Focal Period, holding all else constant. In contrast, a one standard deviation increase in the share of visits to Asian restaurants in Chinese enclaves by international visitors (approximately 2.16 percentage points) is associated with only about a 1 percentage point sharper decline in foot traffic to enclaves, all else being equal.

In the final column, we include the metropolitan area's vote share for President Trump in the 2016 election. This addition eliminates the relationship between antilocution and lost visits. The coefficient for Kung Flu" Search Intensity drops to -0.001, indicating a negligible relationship between antilocution and lost visits when controlling for Trump's vote share. Interestingly, Trump's 2016 vote share and Kung Flu" Search Intensity are negatively related, with metropolitan areas having the lowest Trump vote share searching for "Kung Flu" most intensely. For instance, San Jose, San Francisco, Oakland, San Diego, and Seattle areas show above-average "Kung Flu" search intensities, above-average declines in Chinese restaurant enclave foot traffic, and below-average Trump support. These findings contradict the notion that affinity towards Trump drives the observed enclave effects, suggesting a more complex relationship between political leanings, anti-Asian sentiment, and restaurant patronage during the pandemic.

We speculate that one potential explanation for this finding is that individuals with high baseline anti-Asian bias may not have been those whose bias was most amplified during the pandemic. Those who already held negative views towards Asians may have been less sensitive to additional unflattering information, whereas sentiment could have shifted more negatively among individuals with neutral or positive Asian sentiment at baseline.[33] This

[33] There are indications that negative sentiment towards Asians was more pronounced in areas with lower racial prejudice prior to the pandemic. Google Search Trends, which reports state-level search data only when it surpasses a threshold, shows that 8 states searched "Why Chinese Eat Bats" enough to display data, with the top 5 being Georgia, Illinois, New York, California, and Florida. Only 2 states—California and New

possibility underscores the importance of measuring the *activation* of anti-Asian sentiment and highlights the potential value of measures that capture changes in bias over time. This perspective could also explain why our results on the role of anti-Asian bias differ from those of Honoré and Hu (2022), as their measure, based on state averages of the "Asian Implicit Association Test" (IAT) score from 2018, may not have reflected the dynamic changes in anti-Asian sentiment that occurred during the pandemic.

7 Discussion and Conclusion

Early in the pandemic, reports indicated a rise in inflammatory rhetoric and hate incidents against Asian Americans, signaling increased anti-Asian sentiment. This issue gained prominence following the March 16, 2021 shooting spree by Robert Aaron Long, which resulted in eight deaths, including six Asian women. In response, Congress passed the Covid-19 Hate Crimes Act to address the surge in anti-Asian hate crimes. However, the economic impacts of rising anti-Asian bias on Asian businesses remained unclear. Economic theory suggests that disparities in market outcomes are shaped by the attitudes of those who engage with minority groups. If the pandemic activated sentiment primarily among individuals who do not interact with Asian businesses, the negative economic impacts might be limited. Our study is informative because the changes in foot traffic reveal shifts in the decision-making of consumers who were willing to patronize Asian businesses prior to the pandemic.

Our preferred estimate indicates an approximate 8.8% decrease in visits to Asian restaurants within enclaves relative to the comparison group during the Focal Period. This relative decline cannot be explained by pandemic-related structural changes in the economy, as the period of analysis precedes these developments. Our data also suggests that this pattern is not easily attributed to a general enclave effect, labor supply adjustments, co-ethnic patronage, or early adoption of operational changes (e.g., shift to take-out-only, closure). Analysis using metropolitan area level variation indicates that exposure to recent international travelers, share of Asian population, and integration with the Asian population do not explain the relative decline in visits either. Our measure of activation of anti-Asian sentiment, based

York—searched "Chinese Are Dirty" enough to show data. These search rates are normalized for overall search volume. Similarly, the Stop AAPI Hate National Report identifies California, New York, Washington, Texas, Illinois, and Massachusetts as the top states for hate incidents against Asians. In the Appendix, we show that these rankings are stable even after adjusting for population size.

on Allport's emphasis on antilocution as an early sign of rising prejudice (Allport (1979)), emerges as a stronger predictor of the declines in foot traffic than the aforementioned variables.

An important question is the extent to which anti-Asian bias contributed to the total longer-run decline in economic outcomes beyond our period of study (March to December 2020).[34] Conclusions on this matter vary considerably. The *Small Business, Big Losses* report by the Asian American Federation suggests that Asian-owned small businesses in New York City experienced an approximate average revenue loss of 70% over the longer-run across various types of business including food services, attributing the entire decline to anti-Asian bias.[35] In the short-term housing rental market, Luca et al. (2022) estimate that bookings for Asian hosts fell by 20% more than for White hosts by November 2020, and attribute this disparity to scapegoating and discrimination. In contrast, in the labor market, Honoré and Hu (2022) find a 12 percentage point higher rate of job loss for less educated Asian men than comparable White workers in the second quarter of 2020, but argue that anti-Asian bias is unlikely to be the primary driver of their results.

Our analysis could provide insight into the role of sentiment in the longer-run declines. If our Focal Period estimates represent an upper bound on the impact of changes in anti-Asian sentiment, generalize to the Post-Stay-at-home-Period, and translate to a similar percentage loss in revenue (assuming perfect market competition), then our estimate suggests that at most 14% of the average foot traffic and revenue decline during the Post-Stay-at-home-Period to Asian restaurants inside enclaves could be attributed to changes in sentiment.[36] This suggestive calculation highlights an important role for anti-Asian sentiment while also indicating that other factors—such as access to credit, disparate impacts of Covid-19 policies,

[34] Graphical analysis in academic studies show variability in the dynamic effects over the longer run. For example, Luca et al. (2022) shows a sharp decline in reviews in March for Asian hosts, and then evidence of a partial recovery the remainder of the year. Qin et al. (2023) shows the disparity in physical mobility did not reach its peak until May 2020, and then remained stable the remainder of the year.

[35] This estimate is derived by calculating the weighted sum of the midpoint of each binned revenue loss multiplied by the share of small businesses within that bin. While Chart 2 aggregates all small businesses, Chart 3 suggests a degree of similarity across different types of small businesses in terms of Limited English Proficiency.

[36] Our estimates show that foot traffic to Asian restaurants outside and inside of enclaves fell by 48% and 62% in the first few weeks of March 2020, respectively, aligning with various institutional reports covering longer periods. This back-of-the-envelope calculation is derived by dividing our preferred estimate by the Post-Stay-at-home-Period decline.

operational differences, or other forms of discrimination—likely account for the majority of the foot traffic and revenue declines to Asian businesses observed during the Post-Stay-at-home-Period.[37]

A limitation of our study is the absence of visitor attribute data, which precludes direct examination of whether our results are influenced by potentially higher transmission risk aversion among Asian consumers. To address this limitation, we proxy local market demographics using two factors: (i) the importance of distance in restaurant choice and (ii) the considerable variation in the share of nearby Asian residents across restaurant enclaves. In the Appendix, our analysis reveals comparable declines across Chinese food enclaves with varying proportions of nearby Asian residents, suggesting that Asian consumer behavior is not the primary driver of our results. Additionally, Luca et al. (2022) demonstrates that Asian American guests were *not* responsible for the decline in short-term rental stays with Asian American hosts during the pandemic, indicating that Asian risk aversion was not a driving factor in pandemic-related disparities in another important consumption market.

Another possible explanation for our results is that Asian restaurateurs within enclaves were particularly risk-averse and adopted social distancing measures earlier than other restaurant groups. However, as shown in the Appendix, we find no evidence that Asian restaurants within enclaves transitioned to take-out-only service or closed entirely earlier than others. Alternatively, they may have implemented less observable measures—such as spacing tables six feet apart, improving ventilation, introducing ordering kiosks, or installing partitions—earlier than other restaurants. If consumers prioritized safety, such measures could have increased demand for Asian restaurants within enclaves by positioning them as leaders in mitigating transmission risk. However, this scenario contradicts our findings of greater declines in foot traffic to Asian restaurants within enclaves. Thus, the observed differential decline in patronage would have likely occurred *in spite of*, rather than *because of*, earlier adoption of these types of operational changes.

Our findings are relevant for economic theories of bias. While a standard assumption is that preference-based bias has uniform impacts on members of the minority group, growing evidence suggests that minority members with attributes (e.g., skin tone, vernacular) more

[37]We characterize the back-of-the-envelope calculations as suggestive rather than definitive, given the underlying assumptions involved. It is possible, for example, that negative Asian sentiment intensified over the course of the pandemic, potentially understating its role in our calculation.

distant from the majority group are associated with worse market outcomes (Kreisman and Rangel (2015), Grogger (2011)). Our result that Asian restaurants within enclaves experienced sharper declines in foot traffic aligns with Honoré and Hu (2022), suggesting that the disparate economic impacts of the pandemic on the Asian community interact with perceived assimilation. Although the share of Asian restaurants in enclaves is small, implying small aggregate economic impacts, our findings reinforce the notion that racial attitudes can generate meaningful *intragroup* differences in socioeconomic outcomes.

Another common assumption is that preference-based bias, unlike biased beliefs which update with new information, is generally considered static and less susceptible to change. However, this view is increasingly challenged by empirical research showing that racial sentiment can be activated by external shocks, leading to substantive harm. Economics research has identified a range of potential catalysts including conflicts with international entities (Moser (2012), Gould and Klor (2016)), incendiary media (Ang (2023), Mueller-Smith (2014)), and inflammatory rhetoric (Grosjean et al. (2023)). We observe that Covid-19 influenced the behavior of individuals who had previously chosen to interact with Asians in ethnic enclaves. Less clear is what attributes (e.g., education, age, income) predict responses to said catalysts. Our research suggests richer interplay between ethnic identity and socioeconomic outcomes than what standard economic models of discrimination imply, and we look forward to learning more in future work.

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