Demand for social interactions: Evidence from the restaurant industry during the COVID#19 pandemic

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Demand for social interactions: Evidence from the restaurant industry during the COVID-19 pandemic

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Abstract

We study the heterogeneous impacts of COVID-19 on restaurants in the postlockdown United States, from lens of social interactions. We use the data structure of chain restaurants to disentangle restaurant attributes such as food and service types (which vary across chains) and local market conditions such as infection risks (which vary with each establishment's geographical location). We find that visits to chains with higher social indices experienced larger drops as local new cases increased in 2020, but also faster recovery later when vaccination programs expanded. Moreover, demand for restaurants in city centers recovered faster than demand for those in suburbs.

KEYWORDS

COVID-19 vaccines, resilience, restaurants, social interactions

1 | INTRODUCTION

Consumer amenities have been driving the growth of cities over the past few decades (Carlino & Saiz, 2019; Couture & Handbury, 2020; Glaeser et al., 2001). They are not only an important feature of the density and diversity of city life (Agarwal et al., 2017; Dodds & Dubrovinsky, 2015), but also facilitate daily social interactions in cities (Atkin et al., 2021; Büchel & Ehrlich, 2020). The outbreak of the COVID-19 pandemic in 2020 has unprecedentedly suspended the city lifestyle that relies on consumer amenities. For amenities that thrive on high population density and high level of social interactions such as restaurants (Atkin et al., 2021; Couture, 2013; Davis et al., 2019; Glaeser et al., 2001; Rappaport, 2008), the pandemic hit even harder (Bachas et al., 2020; Banerjee et al., 2021; Chen et al., 2021; Glaeser et al., 2021). However, during the prolonged presence of the virus since its outbreak, demand for these amenities continued to evolve, initiating the recovery of the consumer economy (Li & Wang, 2020; Raj et al., 2020).

Using the restaurant industry as the research context, we examine evolving demand for social interactions during this pandemic and how it heterogeneously shapes postlockdown local consumption activities. Our study focuses on the postlockdown period from July 2020 to May 2021 in the United States. In this period, all states had lifted their lockdown measures and moved toward reopening,[1] although the pandemic continued. Compared with the onset period of the pandemic from March to June 2020, studying the postlockdown period allows us to observe how restaurant consumers spontaneously adapt to the continuously evolving pandemic. In this sense, the timeframe of our study directly complements the research by Glaeser et al. (2021). While Glaeser et al. (2021) focus on restaurant consumption patterns when states implemented and lifted lockdown measures from March to June in 2020, we analyze the period that followed, when policy interventions on mobility became less of a concern and consumers had greater discretion to decide whether to go out and where to eat.

An additional advantage of studying the postlockdown period is that we can track the evolving indicators of the local COVID-19 risk and how they tie to local economic activity during the pandemic. Reported COVID-19 cases was one of the major indicators of the local infection risk at the beginning of the pandemic; then, as real-time data on the vaccination campaign became publicly available, the vaccination rate became another useful indicator of the local risk. Based on this fact, we divide the postlockdown period into two subperiods: the prevaccine period from July to December 2020 when the number of new local cases was the major indicator and the postvaccine period from January to May 2021 when both new cases and the vaccination rate affected people's perception of the infection risk. Under this two-period framework, we estimate *three sets of elasticities* of restaurant visits: those related to new cases in the prevaccine period in 2020 (*case elasticity* in 2020 hereafter) and postvaccine period in 2021 (*case elasticity* in 2021 hereafter), and those related to the vaccination rate in 2021 (*vaccination elasticity* in 2021 hereafter). Empirically, we approximate the local risk using county-level indicators. For new cases, we normalize the number of new cases per 1000 inhabitants in the local population (new cases hereafter). This measure is commonly used in the COVID-19 literature (Banerjee et al., 2021; Brzezinski et al., 2020; Yan et al., 2021; Yang et al., 2020). In the postvaccine period, we also introduce the county-level vaccination rate at the end of each month to approximate the local risk (*vaccination rate* hereafter).

To study the impact of a regional shock such as COVID-19 on the restaurant industry, a common challenge is that independent restaurants tend to have a localized market base. And local restaurant attributes and local shock intensity are both determined by these market attributes. To disentangle local restaurant attributes from local market attributes, we work with a subset of restaurants that belong to large chains. This restaurant chain structure effectively separates these two dimensions in a conceptually orthogonal way: (1) *within each chain*, visits to each establishment vary with the local market in which it is located, with other restaurant attributes such as food, service,

[1]See Figure A1 for the timeline of state-level lockdown measures. During the onset of the pandemic from March to June 2020, most US states and counties adopted lockdown measures to enforce social distancing and reduce the transmission of the virus. In particular, dining in was strictly prohibited during this lockdown period.

and seating environment largely constant across all establishments; and (2) *across chains*, restaurant attributes and dining experiences vary significantly. To simplify the terminology, throughout the paper, we refer to a parent restaurant brand as a chain and an individual restaurant as an establishment.

Using the *within-chain* and *across-chain* structure of our restaurant sample, we propose a two-stage empirical strategy. In Stage 1, we subdivide all the establishments belonging to a specific chain and then estimate the three elasticities for each chain (*chain-specific elasticities* hereafter): case elasticity in 2020, case elasticity in 2021, and vaccination elasticity in 2021. In this stage, our estimation relies on the spatial and temporal variations in the infection risk across counties over time. In Stage 2, we investigate the relationship between each of the three chain-specific elasticities and the chain's attributes. In this stage, our estimation relies on the variation in dining experiences across chains, especially in terms of the level of social interactions.

For the main analysis in this study, we examine dine-in visits to the 100 largest chains and 156,077 establishments belonging to these chains in the United States. Our data on mobile phone-based foot traffic at the establishment level come from SafeGraph Monthly Patterns data from 2019 to 2021. For each chain, we first construct a social interaction index (*social index* hereafter) that reflects the average duration that diners spent in the chain in the prepandemic period. We then study how dine-in visits diverge across chains with different social indices. Consistent with our expectation, our two-stage analysis shows that chains with higher social indices saw larger drops in dine-in visits as the local COVID-19 infection risk increased (proxied by new local cases in 2020), but dine-in visits also rebounded faster in these chains in 2021 as the vaccination rate increased. Additionally, in 2021, we find that although new local cases still influenced people's decision to dine-in at restaurants, it was not as relevant as in 2020. These results suggest that (1) consumers actively adjusted their choice of restaurants to the continuously evolving risk throughout the pandemic and (2) demand for social interactions in restaurants strengthened when the vaccination campaign signaled a lower infection risk.

In addition to the heterogeneous impacts of the pandemic on restaurants with different social indices, we compare the spatial pattern of restaurant visits in city centers with those in suburban areas. We find that when vaccination programs expanded in 2021, establishments in city centers—even those within the same chain—recovered faster than those in suburban areas and that chains with higher social indices benefited more from these programs.

Our study contributes to the literature in three ways. First, we directly contribute to the COVID-19 literature by showing its economic impact. While the existing literature has mostly documented consumers' responses at the beginning of the pandemic, our study spans postlockdown months. Compared with the initial outbreak, when making a decision in the postlockdown period, consumers benefited from the transparent and timely updated data platforms gradually developed and expanded during the pandemic. In addition, in the later stages of the pandemic, consumers benefitted from local vaccination campaigns. Our analysis adds to the extensive body of research on the early responses to the outbreak of the pandemic; indeed, even without mandatory interventions, consumers voluntarily adjusted their economic activities to avoid exposure to the unknown virus (Alfaro et al., 2020; Benzell et al., 2020; Farboodi et al., 2021; Glaeser et al., 2021; Goolsbee & Syverson, 2021; Yan et al., 2021). Our finding of a fast recovery in dine-in visits as vaccination programs began also aligns with Glaeser et al.'s (2021) observation of a quick rise in restaurant consumption after states lifted lockdown policies in the first half of 2020. Additionally, our analysis of consumers' responses to vaccination provides grounded evidence of the benefits of vaccines on local economies. Previous studies of the economic impacts of vaccination are restricted to the positive effects on consumer sentiment revealed from the financial market in the early stage of the vaccination campaign (Acharya et al., 2020; Chan et al., 2021) or the willingness to receive the vaccine and impact on the tourism and hospitality industry (Gursoy & Chi, 2020); only a few studies have documented the impact of vaccination campaigns on everyday economic activities (Tarasewicz & Wilson, 2021).

Second, we add to the literature on the spatial reorganization of economic activities during the pandemic. While the "flight" from city centers to peripheral and less dense areas in the housing market has been widely observed since the outbreak of COVID-19 (Delventhal et al., 2021; Gupta et al., 2020; Liu & Su, 2021;

Ramani & Bloom, 2021), we find no evidence that such spatial patterns will persist in the domain of restaurant consumption. Indeed, we find that in the postvaccine period, restaurants with higher levels of social interactions recovered in both city centers and suburban areas, with those in city centers growing even faster. These findings are consistent with predictions in the literature, suggesting that the consumption benefits from density will continue to persist in city centers—at least in the medium term (Liu & Su, 2021).

Finally, our study adds to the literature on the value of consumer amenities by explicitly studying their social dimension. While eating and drinking establishments are widely acknowledged as places in which people can regularly visit and interact with friends, neighbors, coworkers, and even strangers besides their home and workplace (Oldenburg, 1999), previous economics studies have mostly focused on measuring the quantity, quality, and diversity of restaurants across cities and neighborhoods (Carlino & Saiz, 2019; Couture, 2013; Couture & Handbury, 2020; Kuang, 2017; Rappaport, 2008; Su, 2019). A few exceptions are Atkin et al. (2021) and Andrews (2019): both these studies directly investigate the role of informal social interactions in eating and drinking places and their impacts on knowledge spillovers. Our measure of social interactions differs from these studies.[2] We adopt a "time use" approach to measure social interactions revealed by the length of time that people are willing to stay in a restaurant,[3] conditional on seasonal and regional variations in dining activities.

The rest of this paper is organized as follows. Section 2 outlines our conceptual framework of restaurant choice from the lens of social interactions, Section 3 describes our empirical strategy, Section 4 presents our data and key measures, and Section 5 presents the main results of the empirical analysis. Section 6 concludes and discusses the limitations.

2 | CONCEPTUAL FRAMEWORK

2.1 | Setup

To illustrate the impact of the COVID-19 risk on restaurant visits, we use a simple model of household choice between eating food at home and eating food at restaurants (i.e., dining in). We model the infection risk as an additional cost when a consumer visits a restaurant; the magnitude of this additional cost depends on the infection risk in the local area and types of dining activities in a restaurant.

We assume that (1) a household consumes two types of food products/services: food at home and food at restaurants. We denote the former type as h and the latter as s, and the corresponding quantities are Q_h and Q_s. For food at home, utility comes from the food itself; for food at restaurants, utility comes from a combination of the food and the social interactions associated with the dining experience, and these two components are nonseparable;[4] (2) for both h and s, we only consider their menu prices denoted as P_h and P_s, where we assume that the travel cost is a minor and negligible proportion of the total cost; and (3) the household has a constant food-related budget ($\bar{f}$) and constant taste (α) for the two types of food consumption regardless of the conditions of the pandemic.[5] Putting this together, we model the household's utility from food consumption using a Cobb–Douglas function:

[2]Atkin et al. (2021) use the overlap of mobile devices' positioning in time and space to proxy for the opportunity to interact. Andrews (2019) primarily focuses on social interactions associated with alcohol consumption in bars rather than eating or dining places in general.

[3]The approach aligns with those of Couture (2013) and Su (2019), although they frame "time use" in traveling or staying as the value of amenities in a more general sense.

[4]Intuitively, this means that when dining in a restaurant, consumers need both the food served by the restaurant and the atmosphere for social interactions. The inseparability of these two elements distinguishes dining in from other services such as catering and delivery, which only provide prepared food.

[5]Since our model only focuses on the relative change in prices and quantities rather than the income effects of the virus, we impose a constant food-related budget for simplicity. The constant taste assumption states that the household benefits from each type of food consumption in the same way even though the pandemic has changed the cost side of this consumption.

$$U(Q_h, Q_s) = AQ_s^{\alpha} Q_h^{1-\alpha}$$

$$\text{subject to} \quad Q_h P_h + Q_s P_s \leq \bar{f}$$

where A is the scalar for each unit of utility from food-related consumption.

2.2 | Social interactions and infection risk in restaurant consumption

The prices P_h and P_s reveal the marginal benefits from the consumption of h and s. P_h reflects the benefits of food consumption; for food at restaurants, $P_s = P_h + v(s)$, which states that even for the same food, dine-in restaurants have the additional benefit of social interactions, denoted as $v(s)$. s is the level of social interactions in the restaurant, which is greater than zero and differs across restaurants. $v(.)$ is an increasing function of s and $v(s) \geq 0$.

Exposure to the infection risk varies with the level of social interactions associated with restaurant consumption. Because we focus on comparative statics, for simplicity, we assume that the consumption of food at home has no exposure to the infection risk. When a consumer eats in a restaurant, exposure to the infection risk depends on s and X (the overall local infection risk). The social interactions people previously enjoyed in the restaurant now come with health costs $c(s, X)$, which are increasing with both s and X. Using the superscript post to denote quantities in the postpandemic period, we have

$$P_h^{\text{post}}(X) = P_h, P_s^{\text{post}}(X) = P_s + c(s, X) = P_h + v(s) + c(s, X) \tag{1}$$

2.3 | Elasticity of restaurant visits as a function of social interactions

Solving the Cobb–Douglas consumer problem under this assumption, we have

$$Q_s^{\text{post}} = \frac{\alpha \bar{f}}{P_s^{\text{post}}}, \text{ and} \quad Q_h^{\text{post}} = \frac{(1-\alpha)\bar{f}}{P_h^{\text{post}}} = \frac{(1-\alpha)\bar{f}}{P_h} \tag{2}$$

Under our model and assumptions, food-at-home consumption is always fixed, and we use this quantity as a reference point for changes in food-away-from-home consumption over restaurant attribute s. Cancelling out $\bar{f}$ in Equation (2) and combining it with Equation (1), we have

$$Q_s^{\text{post}} = \frac{\alpha}{(1-\alpha)} \frac{P_h Q_h}{P_s^{\text{post}}} = \frac{\alpha}{(1-\alpha)} \frac{P_h Q_h}{(P_h + v(s) + c(s, X))}$$

Its logarithmic form is

$$\ln Q_s^{\text{post}} = -\ln(P_h + v(s) + c(s, X)) + \phi(\alpha, P_h, Q_h) \tag{3}$$

where $\phi(.)$ aggregates all the terms independent of the risk (X). Translating Equation (3) into the elasticity term, we obtain

$$\frac{\partial \ln Q_s^{\text{post}}}{\partial \ln X} = -\frac{\frac{\partial c(s, X)}{\partial X}}{P_h + v(s) + c(s, X)} = -\frac{1}{P_h/s + 1 + X} \tag{4}$$

The second part of the equation is obtained by inserting the linear functions of $c(s, X) = sX$ and $v(s) = s$, which are chosen to capture the increasing shape of both functions. Then, Equation (4) leads to our main hypotheses:

Hypothesis 1 – *At any given level of risk* ($X > 0$), *the elasticity of restaurant visits to risk levels is always negative.*

Hypothesis 2 – *The ratio between the pure food benefits and social interaction benefits* (P_h/s) *determines the magnitude of the elasticity at any given level of infection risk* (X). *For restaurants with more social interactions and higher* s, P_h/s *is smaller and* $\left|\frac{\partial \ln Q_s^{post}}{\partial \ln X}\right|$ *is larger.*

2.4 | Multiplier effects of social interactions in a city center setting

We extend the model to account for different levels of social interactions as a function of the density of consumer amenities where a restaurant is located. When a restaurant is located in a city center, each unit of social interaction in a restaurant may result in $(1 + \rho)$ units of social interaction for that trip, where ρ models the consumption externality from density. Setting the baseline of such an externality to zero in the suburbs, $\rho > 0$ in the city center. Considering the externality of density, we have

$s^e = (1 + 1_{\{L = center\}}\rho)s$

where L is the location of a restaurant (i.e., in city centers or suburban areas). Replacing s with s^e and denoting the new quantity as $Q_s^{post,e}$ in Equation (4), we have

$$\frac{\partial \ln Q_s^{post,e}}{\partial \ln X} = -\frac{1}{P_h/s^e + 1 + X} \tag{5}$$

s^e is larger than s in city centers; thus, P_h/s^e is smaller and the magnitude of elasticity is larger. Then, Equation (5) leads to the following hypothesis:

Hypothesis 3 – *For restaurants providing the same level of social interactions, those located in city centers have larger elasticity with respect to the infection risk.*

3 | TWO-STAGE EMPIRICAL STRATEGY

We propose a two-stage empirical design to take advantage of the within-chain and cross-chain structure of restaurant chains: within the same chain, the variation comes from where each establishment is located, with the food, service, and dining environment provided by each establishment largely identical; by contrast, across chains, the variation comes from the type of food, service, and dining environment featured by each chain.

We use the largest 100 chains in the United States to carry out this study strategy. On average, each of our sampled chains has 1561 establishments and operates in 486 counties. At any time point, different establishments within a chain are exposed to different levels of the infection risk depending on the local COVID-19 conditions. In Stage 1, we use the variation from this spatial dimension to study the impact of the infection risk on establishment-level restaurant visits and estimate the risk elasticity of a specific chain. Then, in Stage 2, we compare the chain-specific risk elasticities across chains and examine the relationship between risk elasticity and the level of social interactions in each chain. The following subsections describe the implementation of the two stages.

3.1 | Stage 1: Chain-specific elasticity to the infection risk

For chain c, we collect all the establishments that belong to c, and then model the monthly dine-in visits to each establishment of this chain:

$$\ln(\text{Visits}_{iskt}) = \alpha + \beta \ln(X_{kt}) + \gamma \ln\left(\text{Visits}_{iskt}^{2019}\right)$$

$$\ln(\text{Visits}_{iskt}) = \alpha + \beta \ln(X_{kt}) + \gamma \ln\left(\text{Visits}_{iskt}^{2019}\right) + \mathbf{W}_i^{\prime}\boldsymbol{\Phi} + \mathbf{FE_k} + \mathbf{FE_{st}} + \epsilon_{iskt}, \forall\, i \in N^c \tag{6}$$

where we denote each establishment as i, the state and county in which the establishment is located as s and k, the month of observation as t, and the subset of establishments of chain c as N^c. We are interested in β, the chain-specific elasticity of restaurant visits with respect to the county-level infection risk, denoted as X_{kt}. β is the estimate of $\frac{\partial \ln Q_s^{\text{post}}}{\partial \ln X}$ in our conceptual framework in Equation (4). For July to December 2020, we measure the infection risk X_{kt} as new cases per 1000 people in each county in each month. For January to May 2021, X_{kt} includes two variables: new monthly cases per 1000 people and the vaccination rate at the end of each month. In testing Hypothesis 3, we split establishments into city centers and suburban areas and separately estimate the two elasticities for each chain.

We also control for $\text{Visits}_{iskt}^{2019}$, the baseline-level restaurant visits to an establishment in the same month in 2019. $\text{Visits}_{iskt}^{2019}$ controls for the prepandemic popularity and absorbs seasonality in Visits_{iskt}, which is irrelevant to the pandemic. We control for the local market socio-demographic characteristics in W_i, which may be correlated with the local infection risk as well as local restaurant demand. These socio-demographic characteristics are measured at the five-digit zip code tabulation area level (ZCTA5), which includes total population, population density, median household income, the percentage of bachelor degree holders, the percentage of the population aged 25–34, and the percentage of households without dependent children. We also include county fixed effects (FE_k) to control for time-invariant local market characteristics and state-month fixed effects (FE_{st}) to control for major state-level policy changes over the observation period. ϵ_{iskt} is the idiosyncratic error term of each establishment-monthly observation in the subsample of chain c.

3.2 | Stage 2: Social index and risk elasticity across chains

After calculating the 100 chain-specific estimates of β (i.e., $\hat{\beta}$), as described in Equation (6), we fit these estimates using the following linear model:

$$\hat{\beta_c} = \eta + \theta \text{Social Index}_c + \mathbf{Z}_c^{\prime}\boldsymbol{\Gamma} + \varepsilon_c, \forall\, c \in 100 \quad \text{largest chains} \tag{7}$$

where the subscript c denotes a unique chain, Social Index_c is the measure of the level of social interactions provided by chain c, Z_c is the set of additional characteristics of the chain, including price range, service type (beverage only vs. meals), and cuisine category, and ε_c is the idiosyncratic error term of each chain. Social Index_c is the empirical version of our parameter s, the level of social interactions in a restaurant from Equation (4), and thus θ captures the heterogeneous responses to the infection risk across different levels of social interactions.

In Equation (7), because the outcome variable $\hat{\beta_c}$ is an estimate itself, which includes the estimation errors from Stage 1, we use a bootstrapping method to recover the distribution of θ using 1000 trials, resampled with replacement. Consistent with the choice of risk measures in Stage 1, in the prevaccine period, the outcome variable $\hat{\beta_c}$ in Equation (7) is the case elasticity in 2020. In the postvaccine period, as we have two sets of elasticity estimates from Stage 1 (i.e., case elasticity and vaccination elasticity), we separately estimate both following Equation (7).

3.3 | Alternative pooled estimation

An alternative approach to study the heterogeneity in the treatment effects is to pool all the observations and estimate the heterogeneity using the interaction of the treatment variable and attributes driving the heterogeneity (i.e., the infection risk interacting with the social index in our case). Our two-stage design also allows heterogeneity in a more flexible way and with higher dimensions compared with the interaction model pooling all the restaurants.

In pooled models, heterogeneous effects are only allowed for selected variables of the interaction terms. By contrast, in our two-stage design, we treat the observations from each chain as a subsample in Stage 1 and estimate the chain-specific elasticity separately for each chain. In this way, we allow heterogeneous effects across all the chain attributes. Because there are large differences among those chains, this flexible two-stage approach is more suitable for our data. The two-stage model is equivalent to interacting every term in Equation (6) with the dummy for each chain. The 100 chain-specific elasticity estimates from Stage 1 are thus equivalent to the dummy-specific coefficients recovered from interaction terms.

To show the alignment of the two approaches, we also conduct a robustness analysis following the more commonly used interaction model:

$$\ln(\text{Visits}_{icskt}) = \alpha + \beta\ln(X_{kt}) + \zeta\text{Social Index}_c + \theta\text{Social Index}_c \times \ln(X_{kt}) + W_i'\Phi + \text{Social Index}_c \times W_i'\Psi + \gamma\ln\left(\text{Visits}_{icskt}^{2019}\right) + FE_c + FE_k + FE_{st} + \epsilon_{icskt}$$

where the subscript c denotes the chain information of restaurant i, and all other subscripts are identical to those used in Equation (6). The coefficient of $\ln(X_{kt})$ captures the overall impact of the infection risk on restaurant visits and the coefficient of the interaction term $\text{Social Index}_c \times \ln(X_{kt})$ captures the heterogeneity in risk elasticities across restaurants with different social indices. $\mathbf{W}_i$ is the socio-demographic characteristics at the ZCTA5 level, as described in Equation (6). In this model, we also introduce the term $\text{Social Index}_c \times \mathbf{W}_i'$, which allows the preference of restaurant types to vary with the local market characteristics. Besides county and state-month fixed effects that are identical to those introduced in Stage 1, we also include chain fixed effects ($\mathbf{FE_c}$) to control for time-invariant chain characteristics (i.e., the term Social Index_c is omitted). ϵ_{icskt} is the idiosyncratic error term for each establishment-month observation.

4 | DATA STRUCTURE AND CONSTRUCTION OF THE KEY VARIABLES

4.1 | Hundred restaurant chains

For the 100 largest chains in our master sample, we use the SafeGraph Core Places Data as of March 2020. SafeGraph provides a comprehensive list of points of interest (POIs) that cover the whole of the United States. It also collects information on the parent brand of a POI, which refers to the chain to which it belongs whenever applicable. Approximately 30% of restaurant POIs belong to a chain. Our sample includes 156,077 establishments, representing 25% of all the restaurants in the SafeGraph data and 75% of all the establishments belonging to a chain. Geographically speaking, this sample of establishments covers 48 of the US states and the District of Columbia (basically all the mainland states except for Alaska) and 2872 counties. Of the 100 chains, 53 are limited-service restaurants, 34 are full-service restaurants, and 13 are snack and nonalcoholic beverage bars.

We measure dine-in visits to restaurants using the SafeGraph Monthly Patterns Data, which provide monthly aggregated visits based on mobile phone locations tracked at the establishment level. To measure dine-in visits, we exclude visits with a duration in the establishment below 20 min, which are likely to reflect takeout orders rather than dining-in activity, or measurement errors of phones that walk close to a restaurant. We also exclude visits above 240 min, which are likely to reflect employees' visits to the restaurant for work.[6] Panel 1 in Table 1 shows the summary statistics of visits per establishment.

[6]The SafeGraph Monthly Patterns data divide the number of visits into five bins according to duration: 0–4, 5–20, 21–60, 61–240 min, and more than 240 min. We also list the steps used to clean the foot traffic data in Appendix A.2.

TABLE 1 Summary statistics

Variable name	Description	*N*	Mean	SD	Min	Median	Max
Panel 1: Establishment-level monthly visits							
Visits in 2020	Monthly visit count at the establishment level, July and December 2020	954,120	124.85	175.61	0	73	11,341
Visits in 2021	Monthly visit count at the establishment level, January and May 2021	715,845	131.40	192.62	0	73	12,944
Panel 2: Chain-level attributes							
Social index	Chain social index	100	20.59	9.93	9.62	17.50	44.66
Number of establishments	Number of establishments per chain	100	1560.77	2439.86	266	628	15,758
Chain's population	Mean of the ZCTA5-level population where the chain has establishments	100	33,812.98	5002.15	17,418.35	34,205.73	48,167.93
Chain's population density	Mean of the ZCTA5-level population density where the chain has establishments (people per m^2)	100	0.0003	0.0002	0.0000	0.0002	0.001
Chain's median income	Mean of the ZCTA5-level household median income where the chain has establishments	100	32,346.06	3577.88	24,331.61	31,942.37	45,029.29
Chain's percentage of young and educated	Mean of the ZCTA5-level percentage of bachelor degree holders between ages 25 and 44 where the chain has establishments	100	5.36	1.09	2.97	5.24	10.89
Chain's percentage of households without children	Mean of the ZCTA5-level percentage of households without children under 18 where the chain has establishments	100	35.99	1.16	30.96	36.19	39.21
Panel 3: County-level COVID-19 cases and vaccinations							
New cases	Number of new COVID-19 cases per 1000 people, July 2020 to May 2021	48,178	6.02	8.23	0	2.9	147
Vaccination rate	Percentage of people over 18 years old completely vaccinated, January to May 2021	15,636	16.74	17.04	0	10.70	99.90

4.2 | Social index

We construct a social index from the median time a visitor spends in the typical establishment of each chain. We use SafeGraph data in 2019 to construct the business-as-usual level of social interactions. The social index metric follows the time use approach that measures the value of products when their major cost comes from the time spent using them (Goolsbee & Klenow, 2006; Su 2019).[7] The more time people spend in a restaurant, the more likely they are to have a socially amenable time and thus the higher the social value of the restaurant.[8] We define the chain-specific social index of chain c as follows:

$$\text{Social Index}^{c} = E(\text{median duration of stay}^{c}_{ist}|s, t) \quad \forall\ i \in N^{c}, \quad t \in 12 \text{ months in } 2019$$

where we calculate the expectation of the median visitor's duration in establishment i over the 12 months in 2019, conditional on the state (s in which the establishment is located and the month of the year (t when the data are observed. The first condition allows us to control for state-level differences in dining habits and the second allows us to control for seasonality in dining-out activities. Appendix A.3 lists the 10 brands with the highest and lowest social indices. Figure 1 shows the distribution of the 100 chains based on the social index. Texas Roadhouses has the highest social index of 44.7 min and McDonald's has the lowest social index of 9.6 min.[9]

In addition to the social index, we construct other variables that describe the food and services provided by a chain. We collect the meal price and cuisine type of a chain from Yelp using the chain name. We also depict the characteristics of the consumers that a chain typically serves. We aggregate the ZCTA5-level socio-demographic data into chain-level values based on where a chain locates its establishments. All the socio-demographic data come from the 2018 American Community Survey (5-year estimates). For example, to measure the typical local market size that a chain serves, we calculate the mean of the population ZCTA5s in which the chain has an establishment. Similarly, we construct chain-level aggregates for population density, median household income, the percentage of the young and educated population (25–34 years old with a bachelor's degree or above), and the percentage of households without dependent children. Panel 2 of Table 1 summarizes these chain-level characteristics.

Table 2 shows how a chain's social index is related to the chain-specific and local market variables. The first two columns of Table 2 focus on the chain's food and service characteristics. Price is positively correlated with the amount of time people spend in a restaurant. American cuisines are typically more related to chains with higher social indices than are other cuisines. Columns (3) and (4) highlight the local market attributes of a chain. Consistent with the literature (Carlino & Saiz, 2019; Couture & Handbury, 2020; Glaeser et al., 2001), Column (3) suggests that the presence of more households without children is positive and highly correlated with the social index, as is the presence of the young and educated population. Column (4) further adds the population, population density, and median income. Although the coefficients are not significant, their directions largely align with those in the literature: denser areas tend to have a positive correlation with our social index as well as median income.

Additionally, the R^2 values in Columns (1)–(4) suggest that the food and service characteristics of a chain are the most important factors predicting its social index (with $R^2 = 0.594$ in Column (2)). The aggregated local market

[7]Goolsbee and Klenow (2006) use this approach to measure the value of the Internet. Su (2019) uses a similar approach to measure the value of consumer amenities, but focuses on different types of amenities such as museums, restaurants, and grocery stores. Here, we focus on the heterogeneity of consumption activities in the restaurant industry. In addition, measuring the social index at the chain level rather than the establishment level yields a more accurate result to interpret the time spent in a restaurant as a social activity. For instance, we avoid establishment-based flaws or problems with food and people having to wait longer than usual, which is not a social activity itself.

[8]Similar to the rationale in Section 4.1, to restrict visit type to dine-in visits, we exclude observations with a median duration of less than 5 min and greater than 240 min.

[9]This index is the average duration across all the establishments of a chain. If most visits are take-out (less than 20 min by our definition in Section 4.1), this index can be lower than 20. However, in all our analyses in Section 5, we focus on how consumers stop and resume their dine-in consumption in restaurants.

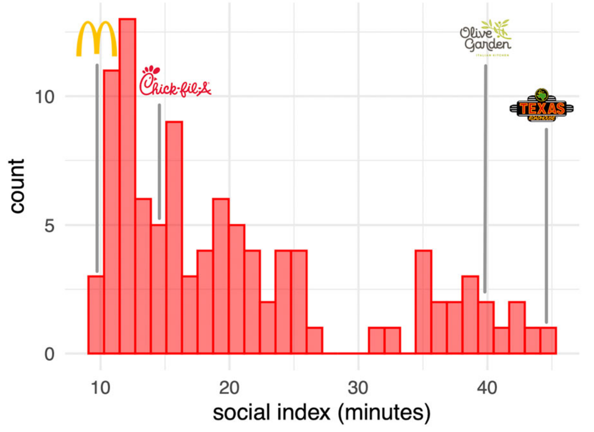

FIGURE 1 Distribution of chains by social index [Color figure can be viewed at wileyonlinelibrary.com]

socio-demographic characteristics of the chain explain less than 0.10 of the variation (with $R^2 = 0.079$ in Column (4) and $R^2 = 0.640$ in Column (5) when both food/service and local market attributes are included). This implies that for our sample of the 100 largest chains, their location choices are less relevant to local demographics. Thus, using establishments within the same chain helps mitigate concerns about confounding factors for local restaurant attributes and COVID-19 conditions.

4.3 | Postlockdown period and risk measures

As stated in Section 3, the postlockdown period has two subperiods divided by the availability of vaccines. In the prevaccine period from July 2020 to December 2020, we use new COVID-19 cases per 1000 people (i.e., *new cases*). We also use monthly new deaths for robustness checks. We collect county-level cases and deaths from Johns Hopkins University and process daily data to the monthly level.

For the postvaccine period from January 2021 to May 2021, in addition to new monthly cases, we use the cumulative percentage of the population fully vaccinated at the end of the month (*vaccination rate*) as a new indicator of how people perceived the risk of engaging in social interactions. We use the county-level vaccination rate published by the Centers for Disease Control and Prevention.[10] Panel 3 of Table 1 summarizes new cases and the vaccination rate. We also explore collinearity of the two variables and find no evidence that they are highly correlated (see Appendix A.4).

5 | RESULTS

5.1 | General patterns: Impact of the pandemic on restaurant visits in 2020 and 2021

To test Hypothesis 1, we present the overall effects of the pandemic on restaurant visits for all the establishments in our sample. In the prevaccine period, we examine the impact of new cases on restaurant visits. In the postvaccine period, we examine the impacts of both new cases and the vaccination rate on restaurant visits. To do so, we

[10]This data set is based on state-reported data; no data are reported for the counties in Texas.

TABLE 2 Chain-level characteristics and chain-level social index relationships

	Dependent variable: Social Index				
	(1)	(2)	(3)	(4)	(5)
Price: High (baseline: Low)	10.689***	6.605***			5.832***
	(1.649)	(1.435)			(1.425)
Price: Medium	26.416***	15.438**			14.135**
	(8.262)	(6.804)			(6.604)
Cuisine: American (baseline: Other)		11.355***			11.437***
		(1.741)			(1.754)
Cuisine: Asian		−0.513			−0.980
		(6.655)			(6.487)
Cuisine: European		18.565***			19.042***
		(6.691)			(6.526)
Cuisine: Mexican		−3.238			−3.466
		(2.495)			(2.447)
Service: Beverages (baseline: meals)		−2.008			−3.704*
		(1.983)			(2.008)
Population young and educated (%)			3.043**	−0.594	1.176
			(1.175)	(4.529)	(2.986)
Households without children (%)			2.410**	1.376	0.546
			(1.107)	(1.785)	(1.170)
ln(Population)				−12.577	−6.364
				(12.715)	(8.405)
ln(Population Density)				2.980	0.078
				(4.028)	(2.660)
ln(Median Income)				24.385	12.330
				(31.482)	(20.889)
Observations	100	100	100	100	100
R^2	0.335	0.594	0.068	0.079	0.640

Note: (a) Price is based on Yelp's price data: high represents those restaurants priced "$$$" or more, medium those priced "$$," and low those priced "$." (b) Population, population density, and median income are the aggregate values for each ZCTA5 zip code in which the chain has establishments. (c)
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

estimate the impact following the model in Equation (10), but dropping the interaction terms, and present the results in Table 3. Column (1) suggests that a 1% increase in new monthly cases was associated with a 2.5% decrease in restaurant visits from July to December 2020. In Columns (2) and (3), we include new cases and the vaccination rate as the single infection risk variables. The results suggest that the impact of new cases on restaurant visits decreased in 2021: when new local cases increased by 1%, restaurant visits declined by 1.5%–1.6%. The vaccination rate became a strong predictor of restaurant visits: when the vaccination rate increased by 1%,

TABLE 3 Overall Effects of the COVID-19 Pandemic on Restaurant Visits

	Dependent variable: ln(Dine-in visits)			
	Prevaccine: Jul–Dec 2020	Postvaccine: Jan–May 2021		
	Cases only	Cases only	Vacc. only	Cases + Vacc.
	(1)	(2)	(3)	(4)
ln(New Cases)	−0.0245***	−0.0157***		−0.015***
	(0.0037)	(0.0039)		(0.0039)
ln(Vaccination Rate)			0.0211***	0.0208***
			(0.0044)	(0.0044)
County FE	Yes	Yes	Yes	Yes
Chain FE	Yes	Yes	Yes	Yes
State × month FE	Yes	Yes	Yes	Yes
Observations	949,932	702,944	702,944	702,944
R^2	0.6079	0.5828	0.5828	0.5828
Adjusted R^2	0.6066	0.5811	0.5811	0.5811

Note: (a) Observations are at the month × establishment level. (b) The control variables not reported in the table include total population, population density, median household income, the percentage of bachelor degree holders, the percentage of the population aged 25–34, and the percentage of households without dependent children in the ZCTA5 area in which the establishment is located. All the models also include monthly visits in 2019 as the baseline control. (b) Robust errors clustered at the county level.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

restaurant visits increased by 2.1%. Column (4) includes both cases and vaccinations in one regression. The estimate of case elasticity is almost identical to that in Column (2) and the estimate of vaccination elasticity is almost identical to that in Column (3). The insensitivity to the specifications indicates that although vaccination reduces transmission, the collinearity between the two variables is not a major concern in our model (as discussed in Appendix A.4). In the following analysis for the postvaccine period from January to May 2021, we estimate case elasticity and vaccination elasticity using a specification similar to that in Column (4), including new cases and vaccination rate variables in one model.

Figure 2 plots the nonparametric patterns of restaurant visits with respect to the changing ranges of new cases and the vaccination rate.[11] These patterns are consistent with the results in Table 3. First, comparing the two left plots, the negative effects of local cases fell in 2021. Second, in the rightmost plot, we find that the effects of the vaccination rate increased linearly from 0% to 70%; after they surpassed 70%, the magnitude of the marginal impacts quickly increased. Such patterns evidence the positive externality of vaccination programs in their later stages when both vaccinated and nonvaccinated individuals felt safer visiting restaurants more frequently.

5.2 | Stage 1 results: Chain-specific elasticities

Following the strategy introduced in Section 3, we first estimate the brand-specific elasticity for each of the 100 chains in our sample. We estimate three elasticities for each chain: case elasticity in 2020, case elasticity in

[11]To estimate the visits in each bin, we include local market characteristics, county fixed effects, state-month fixed effects, and brand fixed effects identical to those in Table 3. In 2021, we control for the vaccination rate (as a continuous variable) when the nonparametric effect of new cases is estimated; similarly, we control for cases (as a continuous variable) when the nonparametric effect of the vaccination rate is estimated.

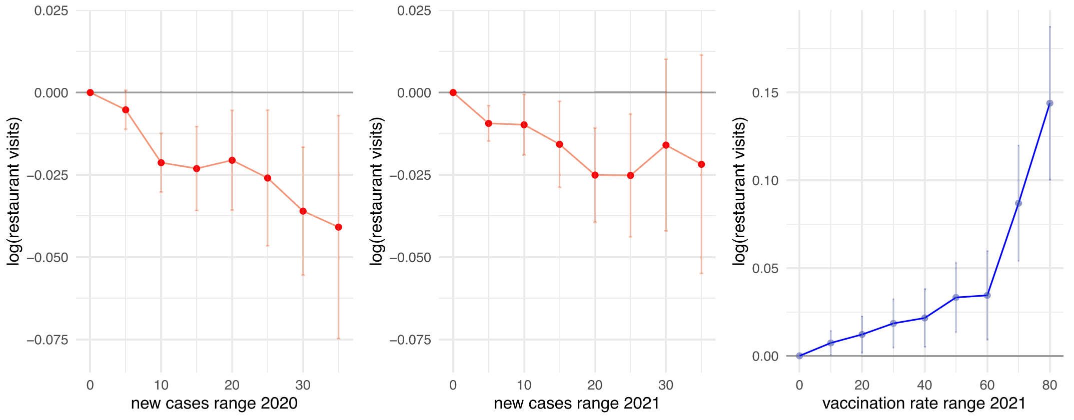

FIGURE 2 Infection risk and dine-in visits, by cases and vaccination ranges. For the two left plots of the cases, the reference bin is [0, 5). For the vaccination rate plot, the reference bin is [0, 10). The outcome variable and fixed effects are identical to those used in Table 3 [Color figure can be viewed at wileyonlinelibrary.com]

2021, and vaccination elasticity in 2021. Table 4 presents the summary statistics of the three sets of chain-specific elasticity estimates. The column named “visits change w.r.t. 1% risk increase” reports the mean of the 100 elasticity estimates. After weighting each chain-specific estimate with the number of establishments of the chain (reported in Panel 2), the means of the three sets of elasticity estimates of the 100 chains are largely consistent with the coefficients in Table 3. To compare the relative importance of case elasticity and vaccination elasticity in the postvaccine period, in the column named “visits change w.r.t. 1 SD risk increase,” we further calculate the impact of a one-standard deviation increase in log new monthly cases or the vaccination rate. After standardization, we find that in the postvaccine period, on average, the magnitude of vaccination elasticity (0.041) was about twice that of case elasticity in absolute value (0.018). The difference in magnitude suggests that the vaccination rate has become a strong factor in consumers' evaluation of the costs and benefits of dining out.

To better illustrate the heterogeneity of chain-specific elasticities, Table 5 presents two sample chains, McDonald's (a well-known fast-food chain) and Olive Garden (a popular casual dining chain). As shown in Columns (1) and (2), in the prevaccine period from July to December 2020, a 1% increase in new local cases predicted a 1.4% decrease in visits to McDonald's, while the same level of infection risk increase predicted a 10.7% decrease in visits to Olive Garden. In Columns (3) and (4), in the postvaccine period from January to May 2021, the increase in local cases no longer significantly affected visits to establishments of both chains and the increase in local vaccination rate positively predicted restaurant visits. When the local vaccination rate increased by 1%, visits to McDonald's increased by 2%, while visits to Olive Garden increased by 9.4%. These findings are consistent with our hypothesis that restaurants with higher social indices have a larger risk elasticity in absolute terms.

5.3 | Stage 2 results: Association between social interactions and risk elasticities

After obtaining the three brand-specific elasticities for each of the 100 chains, we examine the extent to which a chain's elasticities vary with its social index following the methods described in Section 3. Table 6 presents the mean and standard deviation of the coefficients, regressing each of the three chain-specific elasticities against the chain-level social index (i.e., $\hat{\theta}$) based on 1000 bootstrap trials. In Panel 1, the $\hat{\theta}_{2020's}$ are obtained from regressing case elasticity in July to December 2020 against the social index; in Panel 2.1, the $\hat{\theta}_{2021,cases's}$ are obtained from

TABLE 4 Chain-specific case elasticity and vaccination elasticity of 100 chains

	N	Visits change w.r.t. 1% risk increase	Visits change w.r.t. 1 SD risk increase
Panel 1: Simple mean			
Case elasticity in 2020	100	−0.028	−0.025
		(0.005)	(0.005)
Case elasticity in 2021	100	−0.017	−0.013
		(0.005)	(0.004)
Vaccination elasticity in 2021	100	0.043	0.064
		(0.008)	(0.011)
Panel 2: Mean weighted by the number of establishments			
Case elasticity in 2020	100	−0.023	−0.020
		(0.005)	(0.005)
Case elasticity in 2021	100	−0.016	−0.018
		(0.003)	(0.002)
Vaccination elasticity in 2021	100	0.028	0.041
		(0.004)	(0.007)

Note: Standard errors of the chain-specific elasticity estimates are reported in parentheses.

TABLE 5 Elasticity of cases and the vaccination rate for two example chains

	Dependent variable: ln(Dine-in visits)			
	Prevaccine: Jul–Dec 2020		Postvaccine: Jan–May 2021	
	McDonald's	Olive Garden	McDonald's	Olive Garden
	(1)	(2)	(3)	(4)
ln(New Cases)	−0.014**	−0.107***	−0.011	0.007
	(0.006)	(0.029)	(0.007)	(0.025)
ln(Vaccination Rate)			0.020**	0.094***
			(0.009)	(0.030)
County FE	Yes	Yes	Yes	Yes
State × month FE	Yes	Yes	Yes	Yes
Observations	73,530	4992	55,787	3635
R^2	0.56449	0.82582	0.55873	0.85068

Note: (a) Observations are at the month × establishment level. (b) The control variables not reported in the table include total population, population density, median household income, the percentage of bachelor degree holders, the percentage of the population aged 25–34, and the percentage of households without dependent children in the ZCTA5 in which the establishment is located. All the models also include of monthly visits in 2019 as the baseline control. (c) Standard errors clustered at county level.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

TABLE 6 Association between the social index and infection risk elasticities

	(1)	(2)	(3)	(4)
Panel 1	New case elasticity, prevaccine 2020			
$\hat{\theta}_{2020}$	−0.0026***	−0.0024***	−0.0026***	
	−0.0015**	(0.00036)	(0.00048)	(0.00049)
(0.00079)				
Panel 2.1	New case elasticity, postvaccine 2021			
$\hat{\theta}_{2021,cases}$	−0.0010***	−0.0001	−0.0001	−0.0008
	(0.00042)	(0.00051)	(0.00052)	(0.00095)
Panel 2.2	Vaccination rate elasticity, postvaccine 2021			
$\hat{\theta}_{2021,vacc}$	0.0015**	0.0021***	0.0023***	0.0030**
	(0.00068)	(0.00083)	(0.00085)	(0.00150)
Chain-level control variables				
Price levels	No	Yes	Yes	Yes
Snacks/beverage-only	No	No	Yes	Yes
Cuisines	No	No	No	Yes
# of bootstrap trials	1000	1000	1000	1000

Note: (a) The table reports the mean of $\hat{\theta}$ from the 1000 bootstrap trials. Standard deviations are reported in parentheses. Following the description in Section 3, in each of the 1000 trials, we bootstrap within each chain, estimate bootstrapped chain-specific elasticity (bootstrapped Stage 1), and estimate θ using the 100 bootstrapped chain-specific elasticities (Stage 2 with bootstrapped elasticities). In bootstrapped Stage 1, the two elasticities for the postvaccine period (with respect to cases and vaccinations) are simultaneously estimated in one model. In Stage 2, they are treated as two outcome variables, as in Panels 2.1 and 2.2. (b) In each trial, we use four specifications to estimate θ and the set of control variables are listed in the chain-level control variables in Columns (1)–(4). (c) The superscripts *, **, and *** respectively indicate that 90%, 95%, and 99% of the bootstrapped $\hat{\theta}$'s are above zero (Panel 2.2) or below zero (Panels 1 and 2.1).

regressing case elasticity in January to May 2021 against the social index; and in Panel 2.2, the $\hat{\theta}_{2021,\text{vacc}}$'s are obtained from regressing vaccination elasticity in January–May 2021 against the social index.[12]

The four columns represent those specifications with different chain-level control variables in Stage 2. Besides our key variable of interest (i.e., the social index at the chain level), we incrementally add controls for the other chain characteristics in Columns (2)–(4): meal price level (low, medium, and high), service type (meals vs. only beverages), and cuisine type (American, Mexican, Asian, European, and other). Consistent with our expectation, we find that chains with higher social indices had larger elasticity (in absolute value) to new cases in 2020. For the same increase in local cases, chains with higher social indices experienced a sharper reduction in visits. In 2021, while the impact of cases on restaurant visits fell, the differentiation across chains with different social indices was not significant. However, in the same period when vaccines became available, chains with higher social indices had larger positive elasticity, indicating that they recovered faster as vaccination programs expanded locally.

Notably, after controlling for the chain-level characteristics, the difference in vaccination elasticity across the social dimension in 2021 was even larger than the difference in case elasticity in 2020. The asymmetric responses to negative signals (i.e., increasing new cases) and positive signals (i.e., more people being vaccinated) suggest that

[12]For 2021, we simultaneously estimate case elasticity and vaccination elasticity in one model in each bootstrap trial in Stage 1. In Stage 2, we analyze and report the two elasticities separately.

consumers weighted the signals differently in their decision to dine out. While negative signals had similar impacts on all types of restaurant visits, positive signals mostly encouraged visits to restaurants with higher social indices. Our findings suggest that consumers were eager to resume social interactions in restaurants during the postvaccine period. They also echo Glaeser et al.'s (2021) finding of asymmetric responses to the implementation and lifting of lockdown policies.

5.4 | Spatial patterns: City centers versus suburban areas

In this section, we investigate the spatial divide of restaurants in city centers and suburban areas. We divide the establishments in each chain into establishments in city centers and establishments in suburban areas based on the definition of Moreno-Monroy et al. (2020).[13] We then estimate the chain-specific elasticities for these two subsets of establishments separately following the model described in Equation (8) in Section 3. In this section, we only use chains with establishments in both city centers and suburban areas.

Figure 3 summarizes the estimates for case elasticity from July to December 2020 and vaccination elasticity from July to December 2021.[14] As we are interested in social interactions in restaurants, we separately present those chains with higher and lower social indices based on the median social index (approximately 18 min). Consistent with our previous analysis, for both city center and suburban establishments, chains with higher social indices have higher case elasticity and vaccination elasticity in terms of the absolute value.

The differences in restaurants in city centers and suburban areas are also broadly consistent with Hypothesis 3 on the externality of denser consumer amenities in the former, especially in the postvaccine period. As shown in Figure 3a, for chains with higher social indices (plotted in the red striped bars), their establishments in city centers had higher elasticities (in absolute value) than those in suburban areas. The former had an average case elasticity of −0.06 (standard error 0.011), whereas the latter had a case elasticity of −0.03 (standard error 0.025), although the difference in means was not significantly different from zero. By contrast, in the postvaccine period, we find that vaccination elasticity was significantly higher among restaurants in city centers than in suburban areas. The vaccination elasticity for the city center subgroup was 0.057 (standard error 0.013), whereas for the suburban area subgroup, the elasticity was almost zero (0.003) with a standard error of 0.023. Chains with higher social indices were driving these differences: for these chains, the vaccination elasticity in city centers was 0.076 (standard error 0.019) compared with 0.005 (standard error 0.033) in suburban areas, and the difference in means was different from zero at the 10% significance level. This finding suggests a stronger positive externality from denser consumer amenities in city centers when the infection risk declines and shows that consumers returned not only to restaurants but also to restaurants in dense and diverse urban environments.

5.5 | Robustness checks

As described in Section 3, we also estimate the heterogeneity across the three elasticities of interest (case elasticity in 2020 and 2021 and vaccination elasticity in 2021) by pooling all 100 chains and interacting the social index with the local infection risk variables (i.e., new local cases or the vaccination rate). Table 7 lists the results. We first present the pooled results without chain fixed effects for both periods and then the results with chain fixed effects. Comparing Columns (1) and (2) in the prevaccine period with Columns (3) and (4) in the postvaccine period, we find that adding chain fixed effects reduces the magnitude of the coefficients of all the infection risk variables. This is

[13]The city center versus suburban area definition applies to greater city areas. In Appendix Figure A.5, we map the example of New York City.

[14]We do not report case elasticity from July to December 2021 in the main analysis since the vaccination rate became more important for indicating infection risk in 2021.

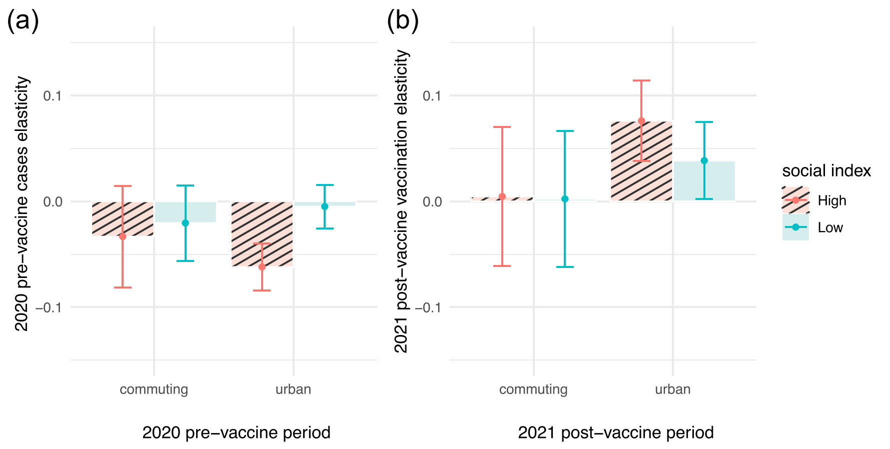

FIGURE 3 Restaurant visits, city centers versus suburban areas, low versus high social indices. (a) 2020 prevaccine period, and (b) 2021 postvaccine period. Error bars indicate 95% confidence intervals. The data used for this plot are presented in Table A.5 [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 7 Heterogeneity of COVID-19 elasticity across the social indices of restaurants

	Dependent variable: ln(Dine-in visits)			
	Prevaccine: Jul–Dec 2020		Postvaccine: Jan–May 2021	
	(1)	(2)	(3)	(4)
Social Index	0.0111		−0.0411***	
	(0.0150)		(0.0147)	
ln(New Cases)	0.0123	0.0044	−0.0351***	−0.0081
	(0.0094)	(0.0095)	(0.0116)	(0.0121)
ln(New Cases) × Social Index	−0.0022***	−0.0017***	0.0012*	−0.0004
	(0.0005)	(0.0005)	(0.0006)	(0.0006)
ln(Vaccination Rate)			−0.0193***	−0.0067
			(0.0067)	(0.0063)
ln(Vaccination Rate) × Social Index			0.0024***	0.0017***
			(0.0003)	(0.0003)
Chain FE	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes
State × Month FE	Yes	Yes	Yes	Yes
Observations	949,932	949,932	702,944	702,944
R^2	0.5826	0.06084	0.5458	0.5833

Note: (a) Observations are at the month × establishment level. (b) The control variables not reported in the table include total population, population density, median household income, the percentage of bachelor degree holders, the percentage of the population aged 25–34, and the percentage of households without dependent children in the ZCTA5 in which the establishment is located. All the models also include monthly visits in 2019 as the baseline control. (c) Standard errors clustered at the county level.

**p* < 0.1; ***p* < 0.05; ****p* < 0.01.

consistent with our expectation as well as our motivation for the two-stage research design that restaurant attributes are correlated with how consumers respond to the infection risk.

For the prevaccine period from July to December 2020, after adding chain fixed effects, in Column (2), the coefficient of the interaction term ln(*New Cases*) × *Social Index* suggests that when the social index increases by 10 min, case elasticity increases by 1.7%. Both the magnitude and the direction of the estimates are consistent with our two-stage results in Panel 1 of Table 6.

For the postvaccine period from January to May 2021, in Column (4), when chain fixed effects are included, we find that Ln(*New Cases*) × *Social Index* was no longer significant, consistent with the findings in Panel 2 of Table 6. For the interaction term Ln(Vaccination Rate) × Social Index, the coefficient is significant, suggesting that when the social index increases by 10 min, vaccination elasticity increases by 1.7%. The result lies in the two-stage range of the estimates in Panel 2.2 of Table 6.

Appendix B provides two additional robustness checks. We first check the robustness of our specification estimating the case and vaccination elasticities in the postvaccine period in 2021. In Appendix B.1, instead of estimating the two elasticities by including both new cases and the vaccination rate in one model (as described in Section 3), we only include one variable at a time and separately estimate them in the two models. This approach yields similar two-stage results to those reported in Table 6.

We then check whether our results hold using alternative infection risk measures. In Appendix B.2, we show that our findings are robust when we (1) replace local new monthly cases per 1000 people with new monthly deaths and (2) replace the fully vaccinated population with the population receiving at least one dose of the vaccine. While the magnitudes vary with alternative measures, the overall patterns across the social indices align with those in Table 6.

Finally, we check if our results are sensitive to the choice of restaurant chain. In Appendix B.3, we expand our sample to smaller chains using the largest 200 chains and repeat the main analysis. Our main finding holds in general, although some smaller chains tend to have noisier estimates of the chain-specific elasticities with respect to both new cases and the vaccination rate.

6 | DISCUSSION AND CONCLUSION

Restaurants play an essential role in providing social places in cities. The COVID-19 pandemic has dramatically interrupted the everyday interactions in these places that people previously enjoyed. Using the restaurant industry as our research subject, our study examines how consumers adapted to the persistent presence of the infection risk in the postlockdown period in the United States from July 2020 to May 2021. Using mobile phone-based foot traffic data on the establishments of 100 major restaurant chains, we estimate the elasticity of restaurant visits to two infection risk measures: new cases throughout the study period and the cumulative vaccination rate since January 2021. Our results suggest that consumers adapted to both the positive and the negative signals of infection risk by adjusting their restaurant visits accordingly. When new cases per 1000 people increased by 1%, restaurant visits dropped by 2.5% in general in the second half of 2020. However, since 2021, the expansion of the vaccination program has become a more important driver in the recovery of restaurant visits, with a 1% increase in the vaccination rate leading restaurant visits to rise by 2.1% from January to May 2021.

We highlight that these elasticities are largely heterogeneous across chains with different social indices. In the prevaccine period, restaurants with higher social indices were hit harder, and dine-in visits to these restaurants recovered faster following the expansion of the vaccination programs in 2021. We also observe an even faster recovery pace in demand for social interactions among restaurants in city centers. These findings present evidence of persistent demand for social interactions and suggest the resilience of demand for short- to medium-term disruptions such as the COVID-19 pandemic.

Our study has several limitations. First, we focus on how consumers respond to the COVID-19 infection risk, rather than the other way around, acknowledging that social interactions in restaurants contribute to the spread of the virus (Chang et al., 2020). For our interest in consumers' responses to local risk levels, our cases and vaccination data are at the county level (i.e., macroindicators received by the economic agent), whereas our outcomes on restaurant visits are at the establishment level (i.e., micro and behavioral outcomes); thus, reverse causality is less of a concern in this empirical setting.

Second, we only implicitly consider COVID-19-related policies. Owing to the monthly granularity of observations, we do not focus on fast-changing policies such as stay-at-home orders rolling out quickly in March and April 2020, then the lifting of these orders from April to June 2020 state by state. Instead of studying consumers' sharp day-to-day responses, our month-level data better suit our research question on generalized and smoothed responses to the COVID-19 infection risk in the later stages of the pandemic.

Third, we elicit a clean estimate of the risk elasticity of restaurant visits holding the other restaurant characteristics constant, using establishments belonging to the largest chains in our analysis. We acknowledge that independent restaurants are more vulnerable during the pandemic than well-capitalized chains (Haddon, 2020). Moreover, independent restaurants serve important social functions in cities (Liang & Andris, 2021). Thus, while our study is based on chains, the risk elasticity of demand for social interactions in independent restaurants could be even larger. For policy implications such as how to allocate government relief to restaurants at different stages of the pandemic, the systematic differences between restaurants with high social index versus those with lower social index should also apply to independent restaurants.

Finally, our analysis focuses on social interactions (i.e., dine-in activities in restaurants). During the pandemic, the restaurant industry has widely adapted to online business such as delivery and takeout to mitigate the negative impacts of the pandemic (Li & Wang, 2020; Raj et al., 2020). Therefore, our estimate of the risk elasticity of social interactions does not represent the overall business of restaurants. Instead, our finding of the faster recovery of dine-in visits indicates that demand for social interactions in restaurants was less likely to be substituted by takeout or delivery. However, for future research, it would be interesting to understand the impact of these alternative dining modes with the rapid penetration of digital platforms. While the pandemic will eventually end, the introduction of these new platform-based services may have a long-term impact on how and where people interact in cities.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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APPENDIX A: ROBUSTNESS CHECKS

A.1 State-wide lockdowns March–June 2020

See Figure A1.

A.2 SafeGraph data cleaning

We reduce noises from SafeGraph by adding the following filters on the raw monthly observations of all establishments:

1. We only use establishments that were observed in each month from January 2019 to May 2021; and we believe that these restaurants are more trackable and reliable in their data generating procedures. Thus, our data set is a balanced restaurant panel with no exit nor entry considered.
2. We notice some abnormally high level of foot traffic in some establishments in some months. We exclude restaurants with any monthly visits (January 2020 to May 2021) three times or higher than the restaurant's 2019 monthly average (approximately 1% of all observations), where we believe these the abnormal peaks in restaurant visits are mostly likely to be measurement or reporting errors.
3. In the specific context of COVID-19, we also exclude restaurants with strictly higher dine-in foot traffic (visits with duration of stay 21–240 min) in April 2020 compared with March 2020. Since in April 2020, most of the states in the US had issued stay-at-home or shelter-in-place orders, we believe these restaurants also had severe measurement/reporting error.

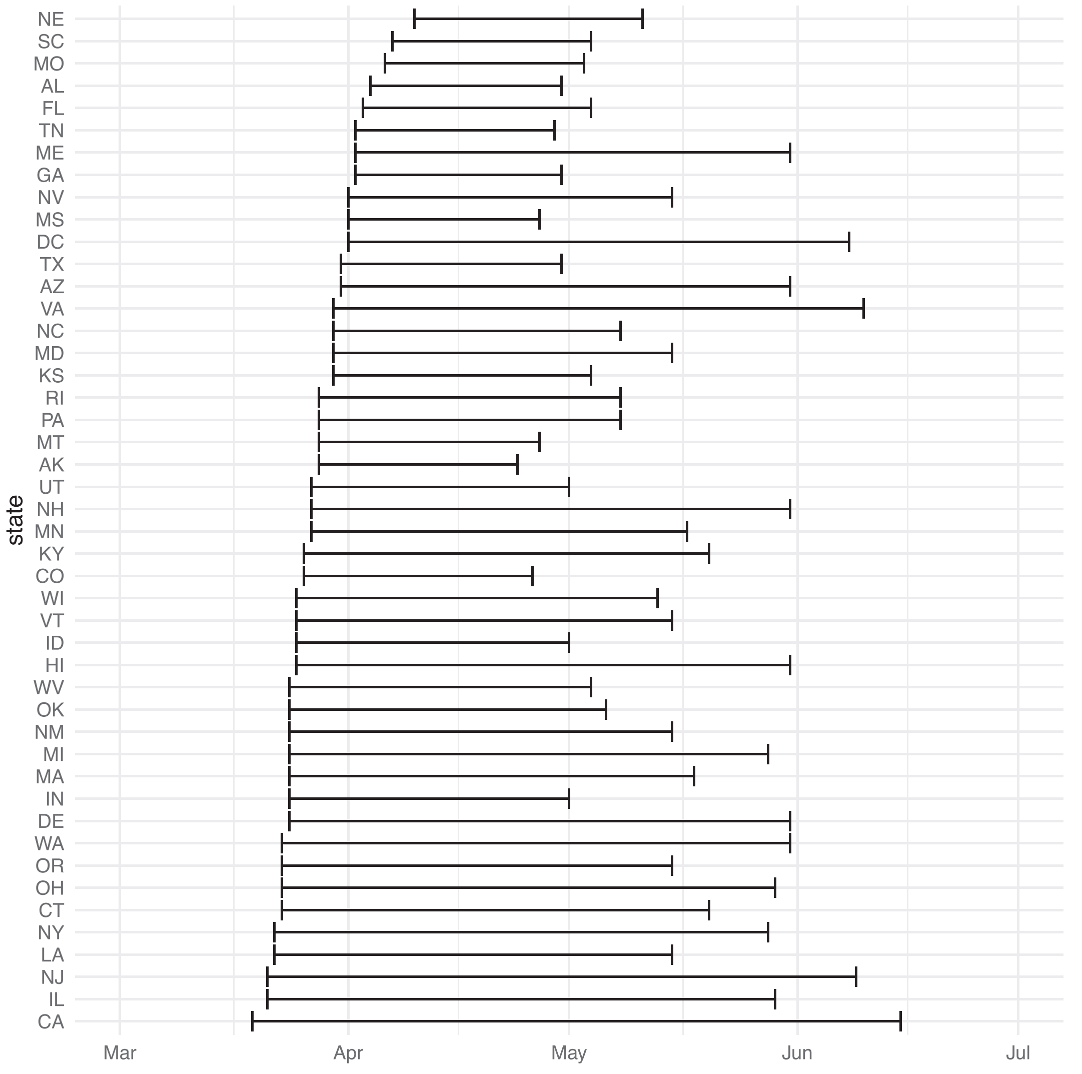

FIGURE A1 State-level start and end dates of stay-at-home orders. Arkansas, Iowa, Nebraska, Wyoming, North Dakota and South Dakota are not included

A.3 Social indices of example chains

See Table A3.

A.4 Relationship between vaccination and cases

Table A.2 presents the correlation analysis of new monthly cases and the vaccination rate from January to May in 2021. In Column (1), without any fixed effects the number of people per thousand completely vaccinated explain only 32% of the new cases. The relationship between the two variables is negative and statistically significant. In the case of adding a county fixed effect (Column 2), the coefficient is lower and county dummies explain more than 32% of the variation in new cases. After adding state-month fixed effects, the correlation between local cases and vaccination rate disappeared, suggesting that mostly of the correlation are driven by inter-temporal co-variance, rather than cross-sectional covariance.

See Table A4.

TABLE A3 Top 10 chains sorted by descending social index

Brand name	Social index	# Stores	# States	# Counties	Price
Top 10 Chains					
Texas Roadhouse	44.662	540	48	419	$$
Cracker Barrel	43.972	642	45	496	$$
Hooters	42.553	269	33	184	$$
LongHorn Steakhouse	41.822	492	40	348	$$$
Outback Steakhouse	40.763	649	44	412	$$
Olive Garden	40.200	832	48	524	$$
Red Lobster	39.851	652	43	471	$$
Applebee's	39.120	1497	48	853	$$
Perkins Restaurant & Bakery	38.634	266	30	197	$
Chili's Grill & Bar	38.268	1125	46	569	$$
Bottom 10 Chains					
Sonic	11.230	3146	45	1189	$
Braum's Ice Cream and Dairy Stores	11.129	273	5	99	$$
Wendy's	10.931	5427	48	1461	$
Bojangles'	10.709	724	11	275	$$
Jack in the Box	10.577	2121	20	243	$
Krispy Kreme Doughnuts	10.564	267	37	194	$
Taco Bell	10.551	6726	48	1747	$
Dutch Bros Coffee	9.818	339	7	78	$
Tim Hortons	9.769	575	11	110	$
McDonald's	9.621	12,243	49	2263	$

TABLE A4 2021 Relationship between new monthly cases and the vaccination rate

	Dependent variable: ln(New cases)			
	(1)	(2)	(3)	(4)
ln(Vaccination Rate)	−0.2838***	−0.3888***	0.0159	−0.0030
	(0.0066)	(0.0052)	(0.0100)	(0.0106)
County FE	No	Yes	No	Yes
State × month FE	No	No	Yes	Yes
Observations	12,695	12,695	12,695	12,695
R^2	0.32445	0.64144	0.75187	0.86377

Note: Observations are at the County × Month level. Standard errors are clustered at county level. ***0.01.

A.5 City centers versus suburban area

See Figure A5.

See Table A5.

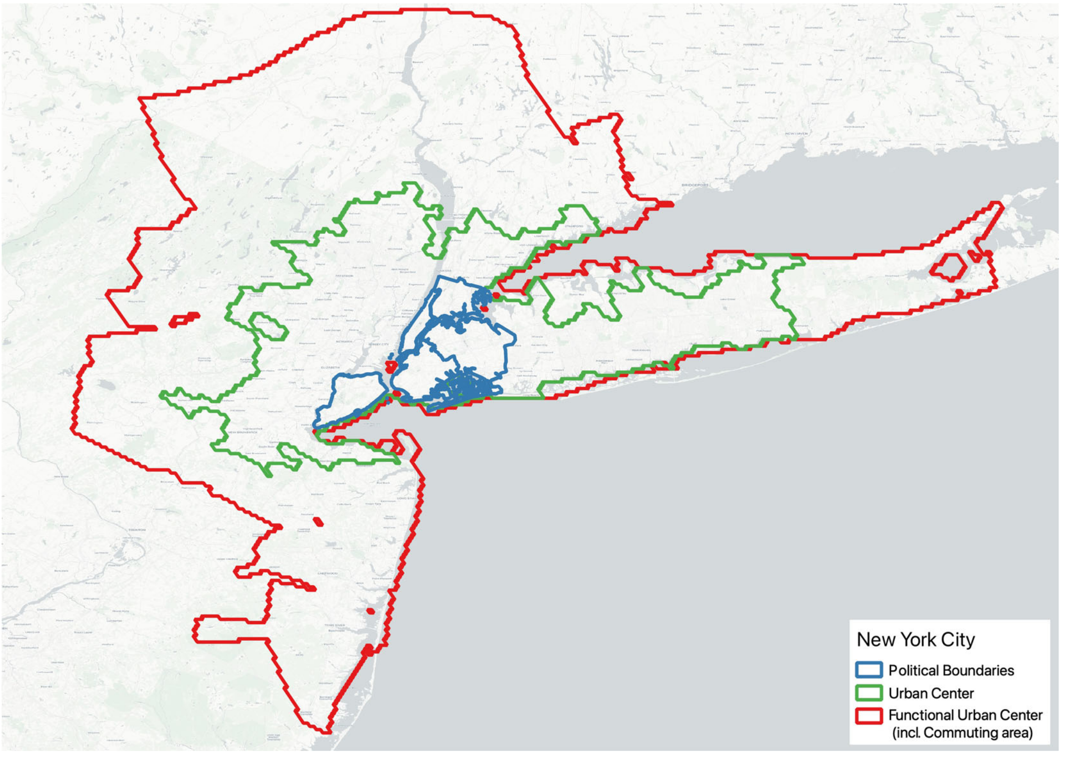

FIGURE A5 NYC city political boundaries versus urban center and suburban area using Moreno-Monroy et al. (2020) definition [Color figure can be viewed at wileyonlinelibrary.com]

TABLE A5 Summary of elasticities by city centers versus suburban areas and high versus low social index

Urban subset	Social index	# of chains	Estimates	SE
2020 prevaccine, case elasticity				
Suburban	High	48	−0.033	0.025
Suburban	Low	52	−0.021	0.018
Center	High	48	−0.062	0.011
Center	Low	52	−0.005	0.01
2021 prevaccine, case elasticity				
Suburban	High	49	−0.055	0.023
Suburban	Low	51	−0.015	0.012
Center	High	49	−0.050	0.012
Center	Low	51	−0.014	0.009

(Continues)

TABLE A5 (Continued)

Urban subset	Social index	# of chains	Estimates	SE
2021 prevaccine, vaccination elasticity				
Suburban	High	49	0.005	0.033
Suburban	Low	51	0.002	0.033
Center	High	49	0.076	0.019
Center	Low	51	0.038	0.018

APPENDIX B: ROBUSTNESS CHECKS

B.1 Risk measures in 2021 separately estimated

See Table B1

TABLE B1 The association between social index and infection risk elasticities (risk measures in 2021 separately estimated)

	(1)	(2)	(3)	(4)
Panel 2.1	New cases elasticity, postvaccine 2021			
$\hat{\theta}_{2021,cases}$	−0.0010**	−0.0001	−0.0001	−0.0006
	(0.000425)	(0.000513)	(0.000521)	(0.000945)
Panel 2.2	Vaccination rate elasticity, postvaccine 2021			
$\hat{\theta}_{2021,vacc}$	0.0015**	0.0021***	0.0023***	0.0030**
	(0.000677)	(0.00083)	(0.000852)	(0.001498)
Chain-level control variables				
Price levels	No	Yes	Yes	Yes
Snacks/beverage-only	No	No	Yes	Yes
Cuisines	No	No	No	Yes
Bootstrap trials	1000	1000	1000	1000

Note: Comparing to Panel 2.1 and 2.2 in Table 6, in bootstrapped Stage 1, the two elasticities for postvaccine period (with respect to cases and vaccination) are estimated in two separate models. In Stage 2, they are treated as two outcome variables as in Panel 2.1 and 2.2. (b) In each trial, we use four specifications to estimate θ and the set of control variables are listed in Chain-level Control Variables in Column (1) to (4). (c) Superscripts *, **, and *** respectively indicate that 90%, 95%, and 99% of the bootstrapped $\hat{\theta}$'s are above (Panel 2.2) or below zero (Panels 1 and 2.1).

B.2 Alternative COVID-19 infection risk measures

See Table B2.

TABLE B2 The association between the social index and infection risk elasticities (alternative risk measures)

	(1)	(2)	(3)	(4)
Panel 1	New death elasticity, prevaccine 2020			
$\hat{\theta}_{2020}$	−0.0112***	−0.0099***	−0.0112***	−0.0111**
	(0.002134)	(0.002491)	(0.002583)	(0.004303)
Panel 2.1	New death elasticity, postvaccine 2021			
$\hat{\theta}_{2021,death}$	−0.0011***	−0.0002	−0.0002	−0.0009
	(0.000425)	(0.000513)	(0.000521)	(0.000953)
Panel 2.2	Vaccination (at least 1 dose) rate elasticity, postvaccine 2021			
$\hat{\theta}_{2021,vacc}$	0.0016***	0.0024***	0.0025***	0.0017
	(0.000703)	(0.000913)	(0.000958)	(0.001438)
Chain-level control variables				
Price levels	No	Yes	Yes	Yes
Snacks/beverage-only	No	No	Yes	Yes
Cuisines	No	No	No	Yes
Bootstrap trials	1000	1000	1000	1000

Note: (a) The table reports the mean of $\hat{\theta}$ from the 1000 bootstrap trials. Standard deviations are reported in parentheses. Following the description in Section 3, in each of the 1000 trials, we bootstrap within each chain, estimate bootstrapped chain-specific elasticity (bootstrapped Stage 1), and estimate θ using the 100 bootstrapped chain-specific elasticities (Stage 2 with bootstrapped elasticities). In bootstrapped Stage 1, the two elasticities for the postvaccine period (with respect to cases and vaccinations) are simultaneously estimated in one model. In Stage 2, they are treated as two outcome variables, as in Panels 2.1 and 2.2. (b) In each trial, we use four specifications to estimate θ and the set of control variables are listed in the chain-level control variables in Columns (1) to (4). (c) The superscripts *, **, and *** respectively indicate that 90%, 95%, and 99% of the bootstrapped $\hat{\theta}$'s are above zero (Panel 2.2) or below zero (Panels 1 and 2.1).

B.3 Alternative sample of chains (largest 200)

Table B3.

TABLE B3 The association between the social index and infection risk elasticities (200 chains)

	(1)	(2)	(3)	(4)
Panel 1	New case elasticity, prevaccine 2020			
$\hat{\theta}_{2020}$	−0.0026***	−0.0026***	−0.0027***	−0.0028***
	(0.000471)	(0.000627)	(0.000649)	(0.000773)
Panel 2.1	New case elasticity, postvaccine 2021			
$\hat{\theta}_{2021,cases}$	−0.0014**	−0.0014*	−0.0015**	−0.0010
	(0.000758)	(0.000823)	(0.000861)	(0.001119)

(Continues)

TABLE B3 (Continued)

	(1)	(2)	(3)	(4)
Panel 2.2	Vaccination rate elasticity, postvaccine 2021			
$\hat{\theta}_{2021,vacc}$	0.0013*	0.0015*	0.0014	0.0025**
	(0.00108)	(0.001201)	(0.001257)	(0.001415)
Chain-level control variables				
Price levels	No	Yes	Yes	Yes
Snacks/beverage-only	No	No	Yes	Yes
Cuisines	No	No	No	Yes
Bootstrap trials	1000	1000	1000	1000

Note: (a) The table reports the mean of $\hat{\theta}$ from the 1000 bootstrap trials. Standard deviations are reported in parentheses. Following the description in Section 3, in each of the 1000 trials, we bootstrap within each chain, estimate bootstrapped chain-specific elasticity (bootstrapped Stage 1), and estimate θ using the 200 bootstrapped chain-specific elasticities (Stage 2 with bootstrapped elasticities). In bootstrapped Stage 1, the two elasticities for the post-vaccine period (with respect to cases and vaccinations) are simultaneously estimated in one model. In Stage 2, they are treated as two outcome variables, as in Panels 2.1 and 2.2. (b) In each trial, we use four specifications to estimate θ and the set of control variables are listed in the chain-level control variables in Columns (1)–(4). (c) The superscripts *, **, and *** respectively indicate that 90%, 95%, and 99% of the bootstrapped $\hat{\theta}$'s are above zero (Panel 2.2) or below zero (Panels 1 and 2.1).