COVID-19 and restaurant demand: Early effects of the pandemic and stay-at-home orders

Abstract

Purpose: This paper aims to evaluate the early effects of the pandemic of coronavirus disease 2019 (COVID-19) and accompanying stay-at-home orders on restaurant demand in U.S. counties.

Design/methodology/approach: Two sets of daily restaurant demand data were collected for each U.S. county: foot traffic data and card transaction data. A two-way fixed-effects panel data model was used to estimate daily restaurant demand from February 1 to April 30, 2020.

Findings: Results show that a 1% increase in daily new COVID-19 cases led to a 0.0556% decrease in daily restaurant demand, while stay-at-home orders were collectively associated with a 3.30% drop in demand. The extent of these declines varied across counties; ethnicity, political ideology, eat-in habits, and restaurant type diversity were found to moderate the effects of the COVID-19 pandemic and stay-at-home orders.

Originality: This study represents a pioneering attempt to investigate the economic impact of COVID-19 on restaurant businesses.

Practical implications: These results characterize the regional restaurant industry's resilience to COVID-19 and identify particularly vulnerable areas that may require supplementary assistance to recover.

Keywords: foot traffic data; restaurant demand; card transaction data; weather-related factors; COVID-19; stay-at-home order

Introduction

The outbreak of coronavirus disease 2019 (COVID-19) has shaken the world in an unprecedented way. This global catastrophe has thus far claimed the U.S. as its largest victim. The latency of the virus and a relative lack of countermeasures in the early stages of transmission resulted in more than 100,000 deaths and 1.7 million cases in the U.S. as of late May 2020 (Dong et al., 2020). COVID-19 is highly transmissible between humans. Its spread can be most effectively controlled by reducing interpersonal contact through physical distancing. In the U.S., physical distancing has been implemented on two authoritative levels: the federal government and state/local governments. COVID-19 was declared a national emergency on March 1, 2020 (White House, 2020), when the domestic outbreak was still in incubation. Then, as infections began to escalate, state and local governments started to implement preventive community measures such as school closures, shutdowns of non-essential businesses, and stay-at-home orders.

COVID-19 has dramatically impacted the restaurant industry nationwide. Although outbreak severity varies by U.S. region and community, nearly every state and local government has enforced physical distancing orders by banning restaurants' dine-in services. While these intervention efforts have minimized personal interaction and alleviated the virus's spread, they have greatly threatened the restaurant industry's survival. According to a National Restaurant Association survey of 6,500 restaurant owners in mid-April, four of 10 U.S. restaurants were forced to close due to financial hardship from the loss of dine-in customers (Sweet, 2020). Strategies to scale back costs apparently cannot sustain the industry; national data show that, compared to the same date last year, the industry's total revenue had plummeted by a harrowing

-63% as of March 29 and was down -40% as of April 30 (Womply, 2020). Alternative off-premise models, such as drive-thru and food delivery, were implemented by restaurants to offset the impact. However, these service models offered an edge for fast food restaurants that had already equipped with digital infrastructure and drive-thru windows; full-service restaurants, however, were not able to quickly adapt to the change, and consequently, took the biggest financial hit (Liddle, 2020).

In the hospitality literature, scholars have explored numerous factors associated with restaurant demand, such as food quality (Namkung and Jang, 2007), price (Kwun and Oh, 2004), location (Yang et al., 2017), and online reviews (Kim et al., 2016b). Among these factors, crisis events represent an uncommon yet critical force, some of which have brought grave consequences to the restaurant industry. Yet only a handful of empirical studies have examined the effects of crises on restaurant demand (Becker, 2009, Koh et al., 2013, Reynolds et al., 2013, Lee and Ha, 2012, Lee and Ha, 2014), and even fewer have adopted rigorous econometric models to do so. To the best of our knowledge, no empirical research has considered the impact of an epidemic crisis on restaurant demand via econometric modeling.

To fill this research gap, we gathered restaurant demand data from two big data sources: foot traffic data and card transaction data. A two-way fixed-effects panel data model was then used to investigate the impacts of the pandemic and stay-at-home orders on restaurant businesses. The moderators of these effects were also scrutinized. We have, therefore, made at least three major contributions to the hospitality literature. First and foremost, this study represents a pioneering effort to unveil the consequences of COVID-19, an unforeseen global pandemic, in the restaurant industry. These estimates can be used to better evaluate economic effects for restaurant businesses and forecast demand based on different pandemic scenarios. Second, we assessed the heterogeneity of COVID-19-related effects by identifying moderators. Our results contribute to the crisis management literature on factors dictating the resilience of restaurant businesses. Last but not least, we demonstrated the potential of using big data as a proxy for traditional business statistics at the national level.

Literature Review and Hypothesis Development

Restaurant demand analysis

Customer demand analysis is particularly important for the foodservice industry, given the perishability of related products and services (Lasek et al., 2016). Predicting trends and exploring the characteristics that influence consumer demand for restaurants can inform restaurant management, strategic planning, and marketing. Such information can also facilitate foodservice-related policymaking and evaluation among governments and other public sectors (Lasek et al., 2016). Extensive research has been conducted on features that inform restaurant demand, as indicated by customers' restaurant choices. These factors can be broadly classified into two categories: (1) micro-level characteristics that are directly relevant to a business and (2) macro-level factors in the external environment that affect business operations.

Among the micro factors influencing restaurant selection, the most important include food quality (Namkung and Jang, 2007), food hygiene and safety (Fatimah et al., 2011), price (Kwun and Oh, 2004), location (Yang et al., 2017), and service quality in the physical environment (Duarte Alonso et al., 2013). Further, online reviews (Kim et al., 2016b) and guest satisfaction (Gupta et al., 2007), which are derived from the above-mentioned aspects, can also influence restaurants' sales and performance. Other micro factors driving restaurant demand include menu design (Wansink et al., 2001), food authenticity (Phung et al., 2019), advertising and promotion (Park and Jang, 2012), branding (Kwun and Oh, 2004), and consumer demographics such as age, income, and household size (Kim and Geistfeld, 2003). Myriad external factors can potentially affect restaurant sales: national economic conditions (e.g., gross domestic product, unemployment rate, and interest rate); national social-demographic characteristics (e.g., population and disposable income); weather; time (i.e., of a day, week, or year); events; government policies; and various crises, such as financial downturns and infectious diseases (Lee and Ha, 2012, Lee and Ha, 2014, Reynolds et al., 2013, Reynolds and Balinbin, 2003, Bujisic et al., 2017, Lasek et al., 2016).

Three types of studies can pertain to restaurant demand analysis depending on how demand is assessed. Most research has taken a micro-level perspective by using individuals' stated choices, behavioral intentions, or revealed choices as a measure of restaurant demand (e.g., Kim and Geistfeld, 2003). Although such work can incorporate individual heterogeneity when seeking to understand and predict restaurant demand, these studies may suffer from limitations. First, consumers' stated choices and behavioral intentions do not necessarily reflect actual behavior, otherwise known as hypothetical bias (Beck et al., 2016). Moreover, customer demand data obtained via self-report surveys, including revealed choice surveys, may be susceptible to self-report bias and errors in participant recall (Beshears et al., 2008). Another group of micro-level studies, which take individual restaurants as the unit of analysis, rely on historical data (e.g., restaurant sales and visits) to depict restaurant demand (Bujisic et al., 2017). These studies can be more accurate and reliable than survey-based studies but often include small sample sizes and focus on only one or a few specific restaurants. The third group of studies focuses on the macro level using aggregated data, such as restaurant sales and visits at the regional or national level, to forecast restaurant demand (e.g., Reynolds et al., 2013). This type of research can account for the influences of external factors on restaurant demand, such as the employment rate and inflation, and offer important implications for policymaking. Thus far, however, few scholars have adopted aggregated data or econometric modeling to analyze restaurant demand (Reynolds et al., 2013), not to mention their applications to COVID-19.

Impacts of crises on restaurants

A crisis is a disruptive and unpredictable event that has potentially adverse effects on a business's ongoing operations, reputation, profitability, growth, and survival (Lerbinger, 1997). Among the many factors influencing restaurant demand, crisis events represent an uncommon yet critical force; some crises may even sabotage the restaurant industry entirely. Crises can arise internally (e.g., from management failures, such as misconduct and deception) or externally from the environment (Lerbinger, 1997). External crises can be further divided into those attributable to sudden changes in the physical environment, such as natural disasters, viral contamination, and environmental pollution; and crises induced by uncertainties in the social environment, such as labor strikes, customer boycotts, terrorism, and economic turmoil (Lerbinger, 1997). Crisis events often have negative impacts on businesses through declining demand and revenue, supply and resource shortages, increasing costs, the disruption of normal operations, and staff layoffs

(Toby and John, 1998). Moreover, different types of crises can be interconnected and cause widespread ripple effects, jointly harming an industry (Okumus and Karamustafa, 2005). For example, the occurrence of natural disasters and epidemic diseases can exacerbate economic crises (Okumus and Karamustafa, 2005, Tse et al., 2006).

A substantial body of research has considered the influences of various crises and crisis management in the broader hospitality and tourism industry; however, much less research exists on these topics within the restaurant sector. Crisis events reported in the restaurant industry include natural disasters, such as Hurricane Katrina in Louisiana in 2005 (Becker, 2009); food safety issues, such as various foodborne illnesses (Seo et al., 2018, Reynolds and Balinbin, 2003, Seo et al., 2014); epidemic diseases like severe acute respiratory syndrome (SARS) and the avian flu (Kim et al., 2020, Tse et al., 2006); financial and economic crises (Lee and Ha, 2012, Lee and Ha, 2014); and terrorist attacks, such as 9/11 in New York (Green et al., 2004). Relevant studies have addressed the effects of crises on restaurants' demand (Becker, 2009, Koh et al., 2013, Reynolds et al., 2013, Lee and Ha, 2012, Lee and Ha, 2014) and financial performance (Seo et al., 2014, Kim et al., 2020), restaurants' crisis management and responses (Green et al., 2004, Seo et al., 2018, Tse et al., 2006), and consumers' responses to crises (Chuo, 2014, Seo and Jang, 2013). Most of these studies focused on the impacts of food safety and economic crises on the restaurant industry. To date, empirical research has not yet considered the impact of the epidemic crisis on restaurant demand. The uncertainty and high risks of the evolving COVID-19 crisis highlight the need to evaluate its lasting effects on restaurant demand to help the industry and public sectors better understand, prepare for, and recover from crises. Further, only one moderator, restaurant type (i.e., fast-food vs. full-service restaurants), has been examined vis-àvis the influences of crises on restaurant demand. Other potential moderators, such as neighborhood sociodemographics, could offer more practical insights into how restaurants at different locations adapt to dynamic crisis situations.

COVID-19 pandemic and restaurant demand

The health belief model (HBM) is a theoretical framework that has been widely used to explain and predict health behaviors in public health research (Champion and Skinner, 2008). The HBM asserts that individuals' disease preventive behaviors can be explained by their risk perceptions and health beliefs (Champion and Skinner, 2008). More specifically, individuals' preventive behaviors can be positively influenced by one's perceived susceptibility to a disease, perceived severity of a disease, self-efficacy in and perceived benefits of taking preventive measures, as well as cues to take actions, and negatively influenced by perceived barriers or costs that prevent individuals from taking preventive measures (Champion and Skinner, 2008). HBM has been used to study various health behaviors in response to various health risks and diseases, including infectious diseases (e.g., Coe et al., 2012). This model can also be applied as a theoretical foundation of the present study to explain consumers' dining out behaviors.

In the context of the present study, consumers' preventive behavior refers to avoiding dining out in restaurants as a way of social distancing to protect oneself from the COVID-19 infectious disease. Perceived susceptibility captures the perceived risks and chances to get infected with COVID-19. Perceived severity refers to the seriousness of negative impacts of COVID-19 infection, which is also related to consumers' risk perception about COVID-19. These risk perceptions could deter consumers from dining out during the pandemic. Risk perceptions play a key role in determining health behaviors (Ferrer and Klein, 2015). They can be shaped by several factors, such as risk communication on mass media, personal health conditions, and cultural background (Kim et al., 2016a). Cues to actions include government policies, including stay-at-home orders and guidelines regarding social distancing. These policies were publicly promoted and enforced to remind or force people to take social distancing actions, including avoiding visiting restaurants. The perceived benefit of avoiding visiting restaurants, i.e., decreased infection risk, could also motivate consumers to do so. However, consumers may not be able to avoid dining out if they have barriers to doing so; for example, essential workers have to go out to work and eat outside during the pandemic.

The foodservice industry is particularly vulnerable to epidemic crises, as it relies on human interaction and gatherings. According to HBM, individuals' preventive behaviors can be positively influenced by several factors: perceived personal susceptibility to infectious diseases; perceived seriousness of the consequences of infection; a perceived sense of control, referring to one's belief in whether they can take effective actions to combat a health risk; personal motivation to maintain good health; and personal risk aversion, referring to one's tendency to avoid uncertainty or risky choices (Chuo, 2014). Moreover, individuals' risk perceptions of an epidemic can be shaped by risk communication via mass media and authorities such as the World Health Organization (WHO) and the federal government. These sources may miscommunicate health-related information such as the confirmed infections, facts about a disease, and whether effective therapeutic or countermeasures exist (Smith, 2006). Risk communication can, therefore, influence the perceived severity and controllability of health risks, even leading to widespread public panic in some cases (Smith, 2006, Chuo, 2014). In the context of COVID-19, restaurant dining could be associated with high perceived personal susceptibility due to the highly infectious nature of human interactions in a relatively enclosed, less ventilated space. Therefore, our first hypothesis is formed as follows:

H1. Escalating infections during COVID-19 lead to lower restaurant demand.

In response to the rapid spread of the pandemic, many countries have implemented strict measures to curtail infections. A stay-at-home order refers to an enforceable executive order from the government, mandating that people stay home as a mass quarantine strategy to control a disease outbreak (NBC Chicago, 2020). Stay-at-home orders have direct and indirect negative impacts on restaurant demand. First, mobility restrictions and restaurant closures have led to a sharp decline in dine-in restaurant demand. Second, stay-at-home orders can indirectly constrain restaurant demand through supply and labor shortages caused by (a) the closure of non-essential businesses that are foodservice industry suppliers (Maghdid and Ghafoor, 2020) and (b) a lack of available employees. Third, an epidemic crisis can spawn other crises, such as an economic crisis, through a ripple effect (Okumus and Karamustafa, 2005, Tse et al., 2006). Last but not least, government actions and policies can influence the general public's risk perceptions (Viscusi, 1995). The above discussion of stay-at-home orders leads to the second hypothesis:

H2. Stay-at-home orders lead to lower restaurant demand.

Restaurants can be generally divided into two types, limited-service restaurants and full-service restaurants. For limited-service restaurants, also known as fast-food or quick-service restaurants, consumers order and pay for their food before eating, and food and drinks can be either consumed on premises, taken away, or delivered. For full-service restaurants, consumers are served at a table and pay after their meal (Reynolds et al., 2013). The influence of an epidemic and associated governmental policies on restaurant demand can vary by restaurant type: because of the less reliance on the service procedure, fast-food restaurants tend to be more resilient than full-service restaurants during epidemic crises. Consumers may possess distinct risk perceptions about dining in fast-food versus full-service restaurants. An epidemic can be spread through physical contact, which is minimized in food procurement at fast-food restaurants: (1) fast-food consumers generally serve themselves with food and drink and clear their own table; (2) fast-food restaurants also offer drive-through and takeout services, which enable consumers to retrieve their food and leave without lingering on premises. Limited physical contact in fast-food service may lead consumers to perceive less risk at these establishments. The necessity to complete the full service cycle at full-service restaurants, on the contrary, increases consumers' risk perception and their reluctance to patronize.

Second, consumers tend to spend less and choose more affordable options during economic downturns if they are earning less income (Bohlen et al., 2010). Fast-food restaurants offer cheaper meal options compared to full-service restaurants and may thus be preferred during economic crises. COVID-19 and the associated nationwide lockdown have caused an economic crisis (Ozili and Arun, 2020), and consumers’ income and spending power have declined accordingly. As such, patrons are more likely to eschew fine dining in favor of cheaper options such as fast food. Empirical studies using historical data have revealed that full-service restaurants are more vulnerable than fast-food restaurants to the negative impact of an economic recession (Lee and Ha, 2014).

In line with the above discussion, we propose the following hypotheses:

H1a. The negative impact of COVID-19 on restaurant demand is moderated by restaurant type, such that fast-food restaurants are less affected than other restaurants.

H2a. The negative impacts of stay-at-home orders on restaurant demand are moderated by restaurant type, such that fast-food restaurants are less affected than other restaurants.

As a nation of immigrants, the U.S. has a highly diverse population in terms of race and ethnicity. Among the various ethnic groups, Asian Americans take up 6% (roughly 20 million), and have been growing at a fast rate (Pew Research Center, 2017). Amid the pandemics, Asian Americans may demonstrate different dining demand patterns from others. First, related to the collectivist cultural background, Asian Americans tend to live in extended households with multiple generations (Pew Research Center, 2017). As a result, Asian Americans tend to have a higher risk perception due to the concern of spreading infectious disease to other family members, especially when they are living with vulnerable family members. Second, Asian culture is characterized by a high power distance, and individuals tend to accept hierarchy and power inequality (Hofstede, 2001). Individuals tend to respect authority and are more likely to follow the rules and regulations set up by authorities (Tyler et al., 2000). Hence, Asian Americans are more likely to follow government policies regarding social distancing. In addition to the cultural background, Asian Americans tend to have higher perceived risks and severity due to communication with connections in Asian countries and exposure to news through Asian media channels regarding the epidemic situation in Asia, where COVID-19 broke out and spread fast at the early stage. As a result, Asian Americans have more information sources regarding the severity of COVID-19 compared to other ethnic groups. Therefore, the following hypotheses are proposed accordingly:

H1b. The negative impact of COVID-19 on restaurant demand is moderated by ethnicity, such that the impact is stronger in communities with more Asian Americans than those with less Asian Americans.

H2b. The negative impacts of stay-at-home orders on restaurant demand are moderated by ethnicity, such that the impacts are stronger in communities with more Asian Americans than those with less Asian Americans.

Family size is another important factor influencing restaurant demand. Scholars have found that an increase in household size is associated with a decline in demand for food consumed away from home due to economies of scale in cooking at home for larger households (Stewart et al., 2004, Kim and Geistfeld, 2003). This phenomenon can be explained by household production theory, which suggests that households attempt to maximize "production" utility through a more effective allocation of various resources, including income, time, and market goods and services (Stewart et al., 2004). In light of the economic difficulty caused by COVID-19 and stay-at-home orders, larger households are more likely to cut their spending on dining out because cooking at home is more economical for larger families than for smaller families. Moreover, consumers from larger households tend to be more concerned about infection risks due to the fear of spreading the disease to other family members, especially vulnerable groups such as children and older adults. Therefore, consumers from larger households are more likely to reduce restaurant visits during an epidemic crisis. We accordingly hypothesize that

H1c. The negative impact of COVID-19 on restaurant demand is moderated by family size in the area, such that the impact is stronger for larger families than for smaller families.

H2c. The negative impacts of stay-at-home orders on restaurant demand are moderated by family size in the area, such that the impacts are stronger for larger families than for smaller families.

According to HBM, knowledge and awareness play a key role in determining individuals' health-related attitudes and behaviors (Van Achterberg et al., 2011). Although the COVID-19 infection is agnostic to political ideology, the bipartisanship in the U.S. has shaped the epidemic growth indirectly through social distance behaviors. As the pandemic is a rare and unprecedented event, how people react to it is largely influenced by news media outlets, public authorities and figures they choose to believe, and people around who have instilled these beliefs in them (Gentzkow and Shapiro, 2006). In this regard, in the early outbreak of COVID-19, people's risk perception could be moderated by the understatement of the disease severity by certain news media and public figures, especially when they share the same political dispositions with these media and figures. Such commonality has been evidenced in the study of risk perception about COVID-19 focused on geopolitics. It has been found that areas with high percentages of Trump voters showed less compliance with social distancing orders in terms of more out-of-home travel and visits to non-essential businesses (Painter and Qiu, 2020). These shaped behavior choices, as a result of moderated risk perception, eventually lead to the regional difference in restaurant patronization. The following hypotheses are hence proposed:

H1d. The negative impact of COVID-19 on restaurant demand is moderated by political ideology.

H2d. The negative impacts of stay-at-home orders on restaurant demand are moderated by political ideology.

Customers' dining habits (e.g., on-site consumption vs. off-site consumption) can also moderate COVID-19's effects on restaurant businesses. Along with the development of Internet technology, such as the emergence of food delivery apps and consumers' changing eating habits, food delivery has become popular in the past decade. Many full-service restaurants have begun offering food delivery services to capture additional revenue and embrace new consumer demand (McKinsey, 2016). With these services, consumers can place online orders either via restaurants' own platforms (e.g., websites or apps) or via third-party food delivery apps. Customers can then either pick up their order on-site or have it delivered to their doorstep. As discussed earlier, eating in restaurants during an epidemic could be perceived as highly risky due to the potential for infection in a relatively closed dining space and required contact with service providers and other patrons. As such, consumers will likely prefer takeaway, food delivery, or drive-through services over on-site dining during an epidemic. Moreover, the stay-at-home orders have directly shifted the restaurant demand from dining into takeaway or food delivery. It has been reported that following the lockdown orders in March and April 2020, restaurants in the U.S. that remained open for delivery experienced a significant increase in food delivery orders on Uber Eats, a food delivery platform (Raj et al., 2020). We, therefore, propose the following hypotheses:

H1e. The negative impact of COVID-19 on restaurant demand is moderated by local residents' past dining habits, such that the impact is stronger in areas where a larger proportion of residents choose to dine in at restaurants.

H2e. The negative impacts of stay-at-home orders on restaurant demand are moderated by local residents' past dining habits, such that the impacts are stronger in areas where a larger proportion of residents choose to dine in at restaurants.

The U.S. restaurant industry is highly diverse in terms of ethnicity-cuisine type (e.g., Mexican and Italian restaurants) and general food type (e.g., vegetarian food and seafood). Consumption motivations can be broadly divided into two categories, utilitarian and hedonic motivations (Babin et al., 1994). Utilitarian motivation refers to purchasing a product for functional, economic, rational, or practical benefits, while hedonic motivation refers to purchasing a product for emotional and experiential benefits, such as dining for fun, enjoyment, entertainment, or novelty (Martínez-López et al., 2014). Different from utilitarian consumption, hedonic consumption is more likely to be impacted by external factors. In a market with diverse restaurant types, consumers may try different types of restaurants for novelty or variety-seeking purpose (Ha, 2018), which also belongs to hedonic motivation as consumers seek for different and novel dining experiences. In the context of COVID-19 pandemic, when non-essential activities are discouraged as social distancing measures, consumers are more likely to reduce restaurant consumption out of hedonic motivations. Hence, we hypothesize that:

H1f. The negative impact of COVID-19 on restaurant demand is moderated by restaurant type diversity, such that the impact is stronger in more diversified markets in terms of restaurant types.

H2f. The negative impacts of stay-at-home orders on restaurant demand are moderated by restaurant type diversity, such that the impacts are stronger in more diversified markets in terms of restaurant types.

Research Methods

Data sources for restaurant demand

We gathered the daily restaurant demand in two separate sources: the daily foot traffic data and the daily card transaction data. We used the two types of data, as they represent two very different aspects of restaurant demand. The foot traffic data were the number of restaurant patronage aggregated daily by county, representing the frequency of consumers visiting a restaurant; the transaction data were the total restaurant sale aggregated daily by zip code, representing consumer spending at the restaurant. As there has been no consensus in the measure of restaurant demand, these two datasets complement each other in estimating the demand. More importantly, they represent the consumer behavior of two different user groups, as articulated below.

The first data, the daily foot traffic data, were employed to represent the restaurant demand from general consumers. Recent studies on the effects of COVID-19 employed the foot traffic data to estimate the demand in various industries (e.g.,White et al., 2020). The data, collected from an open-access platform (visitdata.org), consisted of store visits from a panel of 13 million always-on, opted-in users aggregated on the county level across the entire U.S. To improve the representativeness of the data, the number of visits was adjusted based on the data panel's size and the age-gender distribution. The original visit data were further refined with respect to the food industry (i.e., restaurant and food away from home). Also, due to the small sample in many counties, we further refined the data in 1,882 counties across the U.S.

The second data, sourced from a commercial data provider (facteus.com), consisted of three major types of card transactions at restaurants: (1) transactions from the so-called "challenger banks" (i.e., small, mobile-only banks) debit cards and general-purpose debit cards (i.e., pre-loaded debit cards purchased at retailers); (2) transactions from payroll cards, which are debits cards distributed by employees via direct deposit; (3) transactions from government cards, which are cards issued by governments for distributing alimony and relief stipends. Thus, the transaction data mainly represent restaurant demand of low-income populations, who are also susceptible to financial hardship during COVID-19. Because the transaction data were originally coded with cardholders' residential zip codes, we further aggregated them on the county level for the consistency in the analysis unit.

Figure 1 presents a scatter plot overlapping the foot traffic and transaction data (in logarithm). The figure reveals a strong positive statistical association between the two datasets with a correlation coefficient of 0.862 (p-value < 0.01). This high correlation reveals that there are no obvious differences in the restaurant demand between user groups or between the total visits and total spending.

(Please insert Figure 1 about here)

Econometric models and variable operationalization

We used a two-way fixed-effects panel data model (Zervas et al., 2017), akin to the difference-in-difference setup, to test our research hypotheses. The model is specified as follows:

$$\ln Y_{it} = \beta_1 \cdot \ln new\_cases_{it} + \beta_2 \cdot stay\_at\_home_{it} + \mathbf{X}_{it}\delta + \mu_i + \tau_t + \varepsilon_{it} \qquad (1)$$

where *i* indicates the county of observation and *t* indicates the day of observation from February 1 to April 30, 2020. Based on the selected data, the dependent variable $\ln Y_{it}$ represents either the log of foot traffic visits to restaurants in county *i* at day *t* (from February 1 to April 30, 2020) or the log of total restaurant transactions from cardholders in county *i* at day *t* (from February 1 to April 17, 2020). Note that we collected foot traffic visits to different restaurant sub-categories, such as fast-food restaurants; however, sub-category data were unavailable for transaction data. The two major variables of interest in this model were $\ln new\_cases_{it}$, indicating the log number of daily new confirmed COVID-19 cases in each county (https://www.nytimes.com/interactive/2020/us/coronavirus-us-cases.html); and $stay\_at\_home_{it}$, reflecting whether a stay-at-home order was in effect in a given county based on state and county restrictions (https://github.com/COVID19StatePolicy/SocialDistancing and https://ce.naco.org/?dset=COVID-19&ind=Emergency%20Declaration%20Types). We tested the estimated coefficients of β_1 and β_2 to test H1 and H2. To test H1a and H2a, we used the dependent variables of restaurant sub-categories, their point and interval estimates of β_1 and β_2, to determine if the 95% confidence interval overlapped. $\mathbf{X}_{it}$ indicates different control variables in the model that help explain daily restaurant demand in each county. In the model, μ_i represents the county-specific effect for each county that is invariant during the research period; any time-invariant county-specific factors shaping restaurant demand were captured in μ_i, such as location, population density, county infrastructure, and urbanization (Yang et al., 2017). τ_t

denotes the day-specific effect for each type of data that is invariant for each county in a single data category; for example, seasonality, day-of-week effect, holiday effect, and any nationwide policy change were captured in the day-specific effect of τ_t (Brzezinski et al., 2020). Lastly, ε_{it} is the normal error term.

Regarding the control variables $\mathbf{X}_{it}$, we included the following:

- ln*sum_rainfall*$_{it}$: the log number of the sum of rainfall in a given county each day. Data were collected from GRIDMET: University of Idaho Gridded Surface Meteorological Dataset (https://developers.google.com/earth-engine/datasets/catalog/IDAHO_EPSCOR_GRIDMET). According to the literature, the precipitation level, as a barrier to travel outside, is negatively associated with restaurant demand (Bujisic et al., 2017).
- *temperature*$_{it}$: average temperature (in Fahrenheit) in a given county each day. Data were collected from GRIDMET. Temperature is one of the most important factors in restaurant demand forecasting (Lasek et al., 2016).
- *temperature2*$_{it}$: the square of average temperature in a given county each day. This variable helps capture the non-linear effect of temperature on restaurant demand (Bujisic et al., 2017).
- *rest_restriction*$_{it}$: the presence of government restrictions on restaurant businesses, where *rest_restriction* = 1 indicates that these restrictions are in effect and *rest_restriction* = 0 otherwise. Policy data were collected from https://github.com/COVID19StatePolicy/SocialDistancing. Restaurant restrictions vary

across counties and states, and typical restrictions include limited operations for off-site consumption and mandated on-site capacity reduction (i.e., ten patrons or fewer).

To further test the remaining research hypotheses, we added the moderating variable Z_{it} to our models as follows:

$$\ln Y_{it} = \beta_1 \cdot \ln new\_cases_{it} + \gamma_1 \cdot Z_i \cdot \ln new\_cases_{it} + \beta_2 \cdot stay\_at\_home_{it} + \mathbf{X}_{it}\delta + \mu_i + \tau_t + \varepsilon_{it} \quad (2)$$

$$\ln Y_{it} = \beta_1 \cdot \ln new\_cases_{it} + \beta_2 \cdot stay\_at\_home_{it} + \gamma_2 \cdot Z_i \cdot stay\_at\_home_{it} + \mathbf{X}_{it}\delta + \mu_i + \tau_t + \varepsilon_{it} \quad (3)$$

where Z_i indicates one of the following moderating variables:

- $asian_i$: percentage of Asian population alone in a given county. Population data for 2019 in each county were drawn from U.S. Census and American Community Survey data. This variable was used as a moderator to test H1b and H2b.
- $\ln familysize_i$: log of the average family size in a given county in 2019. Data were taken from the U.S. Census and American Community Survey data. This variable was used as a moderator to test H1c and H2c.
- $vote\_dem_i$: vote percentage for the Democratic party in each county in the 2016 presidential election, and this variable measures the political ideology of the county. Data were collected from https://townhall.com/election/2016/president/. This variable was used as a moderator to test H1d and H2d.

- *eat_in$_i$*: percentage of customers choosing to dine in at a restaurant in a given county in 2019, and it reflects the dining habit of residents before the pandemics. Data on the percentage of dine-in customers of restaurants were gathered from the MRI Simmons Survey of the American Consumer (https://www.mrisimmons.com/solutions/national-studies/survey-american-consumer/). This variable was used as a moderator to test H1e and H2e.
- *restaurant_diversity$_i$*: the restaurant diversity index of the county defined as $D = 1 - \sum_{e=1}^{m}(S_e)^2$ (Bakens and de Graaff, 2020), where S_e indicates the percentage of American, Asian, Mexican, fast-food, seafood, and vegetarian restaurants in each county, respectively. Data were collected from factual.com, the leading data vendor providing the data on points of interest (REFERENCE UNDISCLOSED DURING THE REVIEW PROCESS). This variable was used as a moderator to test H1f and H2f.

Data description

Figure 2 provides raw data on nationwide daily restaurant visits based on Foursquare foot traffic data since February 1, 2020. As shown in the time-series graph, daily visits plummeted in mid-March but began to bounce back in late-April. Figure 3 displays the geographic pattern in restaurant visit change from February 1 to April 30 in all contiguous U.S. states. Restaurant visits declined dramatically in counties in several locations, such as the Boston–New York–Philadelphia–D.C. corridor in the northeast, Florida’s coastal region, the area surrounding Lake Michigan in the Midwest, and near Los Angeles in southern California.

(Please insert Figure 2 about here)

(Please insert Figure 3 about here)

Table 1 presents descriptive statistics for the dependent, independent, and moderating variables. For ln*visits_fast_food*, foot traffic data on the fast-food restaurant sub-category were only available for a small subset of counties. Variance inflation factors for independent variables were well below 3.0, indicating the absence of major multicollinearity issues in our study (Dormann et al., 2013).

(Please insert Table 1 about here)

Empirical Results

We first took foot traffic data as the dependent variable and then switched to transaction data for a robustness check. Table 2 presents estimation results from our baseline models based on foot traffic data. In addition to control variables, Model 1 included ln*new_cases* (number of daily new confirmed COVID-19 cases), Model 2 included *stay_at_home* (implementation of stay-at-home order), and Model 3 included both. The estimated coefficient varied negligibly, confirming the robustness of our model specification. We used the results of Model 3 to interpret coefficient estimates. First, the estimated coefficient of ln*new_cases* was -0.0556 and statistically significant at the 0.01 level. This finding suggests that a 1% increase in daily confirmed COVID-19 cases in a county led to a 0.0556% increase in restaurant demand as measured by foot traffic data. This result lends support to H1. The other variable of interest in Model 3, *stay_at_home*, was estimated to be negative and statistically significant; as such, a stay-at-home order resulted in a 3.30% decrease in restaurant demand. This finding corroborates H2. Regarding the control variables in Model 3, ln*sum_rainfall* and temperature were each estimated to be statistically significant. Estimation results showed that a 1% increase in daily total rainfall led to a 0.00437% decrease in restaurant demand, while a 1-degree increase in average daily temperature resulted in a 0.208% boost in restaurant demand. The quadratic term was statistically significant; however, the turning point was around 0 degrees, beyond the data range in our sample. Therefore, the effect of temperature remained monotonic on restaurant demand during the research period (February to April 2020). Lastly, the coefficient of *rest_restriction* was estimated to be -0.0608, revealing that a restaurant restriction order accounted for a 6.08% decline in restaurant demand after controlling for other factors.

(Please insert Table 2 about here)

Models 4–6 were estimated using the same specification as in Models 1–3 based on foot traffic data from fast-food restaurants. The variables ln*new_cases* and *stay_at_home* were each estimated to be negative and statistically significant in the models. Based on the estimates in Model 6, the coefficient of ln*new_cases* and its 95% confidence interval were lower than their counterparts in Model 3; therefore, H1a was supported, indicating that the pandemic influenced restaurant demand less for fast-food restaurants. However, the 95% confidence interval of *stay_at_home* overlapped with that in Model 3, lending little support to H2a. Interestingly, the coefficient of *rest_restriction* was not statistically significant in Models 4–6. One possible reason is that customers became accustomed to takeout and drive-through services at fast-food restaurants, which rendered the effect of restaurant restrictions on eat-in services less noticeable.

Table 3 presents the estimation results of models that included moderating variables. To avoid confusion, each model contained only one interaction term with the moderating variable. The moderating effect of ethnicity (*asian*) was examined in Models 7 and 8. The negative and significant coefficient of the interaction term in the models supports H1b and H2b, showing that restaurants in communities with more Asian American presence were more affected by COVID-19 and stay-at-home orders. Models 9 and 10 consider the moderating effect of family size (ln*family_size*); however, the interaction term was not statistically significant in the model, rejecting H1c and H2c. Therefore, family size was not a significant factor moderating the effect of COVID-19. Models 11 and 12 incorporated political ideology (*vote_dem*) as the moderating variable, and ln*new_cases***vote_dem* and *stay_at_home***vote_dem* were statistically significant and negative. This result corroborates H1d and H2d in that the impacts of COVID-19 and stay-at-home orders were more substantial in counties with a higher vote percentage for the Democratic party. Models 13 and 14 included eat-in habit (*eat_in*) as the moderating variable; its moderating effect was found to be insignificant as indicated by the insignificant coefficients of the interaction term. Therefore, H1e and H2e were rejected. Lastly, Models 15 and 16 consider the moderating effect of restaurant type diversity (*restaurant_diversity*); the negative and significant coefficients of interaction terms lend support to H1f and H2f.

(Please insert Table 3 about here)

Table 4 presents estimation results for a robustness check of our findings using transaction data as the dependent variable. Note that due to data unavailability for different restaurant sub-categories, we could not test H1a or H2a using transaction data. In Model 17, the significant and negative coefficients ln*new_cases* and *stay_at_home* supported H1 and H2. Similar to our results based on foot traffic data, H1b, H2b, H1d, and H2d were accepted while H1c and H2c were rejected. One notable difference concerned H1e and H2e: as shown in Models 24 and 25, the interaction term with moderator *eat_in* was estimated to be statistically significant and negative, showing that greater losses in restaurant demand were observed in counties where customers were more accustomed to eat-in dining. This result substantiates H1e and H2e. A possible reason for this pattern is that county-level card transaction data are based on card users' place of residence rather than the business location of transactions; as such, the data match the geographic unit of eat-in habit data based on county residents. Lastly, the moderator *restaurant_diversity* was estimated to be insignificant in Models 26 and 27. This discrepancy can be explained by the limitation of our credit card data source, and the data may not fully capture the demand of certain types of high-end restaurants.

(Please insert Table 4 about here)

Conclusion

In this study, we examined the early effects of the COVID-19 pandemic and stay-at-home orders on daily restaurant demand in U.S. counties from February 1 to April 30, 2020. Two big data sources were used, specifically foot traffic data and card transaction data from restaurant businesses. After controlling for weather factors and restaurant business restrictions, a two-way fixed-effects model revealed that COVID-19 significantly affected restaurant demand. Based on the foot traffic restaurant visit model, we found that a 1% increase in daily new COVID-19 cases led to a 0.0556% decrease in restaurant demand while stay-at-home orders were associated with a 3.30% demand decline. More specifically, our results show that the negative effect of COVID-19 was smaller for fast-food restaurants compared to full-service establishments. The negative effect was also larger in areas with a larger Asian American population, a higher vote percentage for the Democratic Party, a higher proportion of eat-in restaurant customers in the previous year, and a higher level of restaurant type diversity.

Some research hypotheses were not supported by our empirical results. H2a was rejected while H1a was accepted. While the negative impact of COVID-19 pandemics differs between fast-food and all restaurants, that effect of stay-at-home orders is largely similar after controlling for other pandemic-related factors. One possible reason is that because of the COVID-19 pandemic situation, most of restaurant customers had already switched to off-site consumption, making fast food restaurants suffering the same level as other restaurants after the subsequent stay-at-home orders. Furthermore, neither H1c nor H2c was supported, and the negative impacts of COVID-19 pandemic and stay-at-home orders are not moderated by family size in the area. One possible reason is that although larger families are less likely to patron restaurants amid pandemics for economic concerns, the health concerns on COVID-19 infection can substantially outweigh the economic concerns. As a result, family size is not moderating the effect of pandemics.

Our research represents a novel effort to understand the economic impact of COVID-19 on the restaurant industry. This study contributes to the restaurant demand forecasting literature by providing useful insights into the elasticity of restaurant demand under the COVID-19 pandemic. More importantly, based on the HBM framework, our study proposed and confirmed various factors moderating the negative effect of COVID-19 to enhance understanding of restaurants' resilience against pandemic crises under different conditions, which contributes to the current literature in the foodservice industry. For example, we recognized political ideology as a moderating factor on the economic impact of pandemics, echoing McGrath (2017) that political beliefs can shape people's economic behavior through the "perceptual screen." Also, we found restaurant type diversity as another moderating factor. Although restaurant diversity improves the region's business vitality and attractiveness (Zheng et al., 2016), this can lead to more severe economic shock during the crisis (e.g., pandemics). Furthermore, our work is one of only a few empirical studies in the restaurant domain to adopt rigorous econometric models in restaurant demand analysis using a nationwide multi-area sample. The two-way fixed effects modeling enables estimating causal effects from panel data while controlling for unobserved unit-specific and time-specific factors simultaneously (Zervas et al., 2017). Last but not least, we demonstrated the usefulness of big data sources in monitoring daily restaurant demand. Foot traffic data and card transaction data were found to be highly correlated, and they provided crossed reference and robustness checks on our study results. Compared to traditional industry statistics, big data sources provide records of consumers' real actions and cover a much larger sample base, hence providing more reliable and comprehensive results about consumer behavior (Song and Liu, 2017). Big data also allows for spontaneous monitoring of demand with more granular insights into business sub-categories.

These empirical results provide several important practical implications. First, the moderators we identified can contextualize the resilience of the regional restaurant industry to COVID-19. Figure 4 presents a restaurant resilience index we estimated from our econometric results based on moderators (WEB LINK UNDISCLOSED DURING THE REVIEW PROCESS). This index can help government entities and other stakeholders pinpoint areas that are particularly vulnerable to COVID-19. Appropriate resources should be allocated to restaurants in locations with a lower resilience level has highlighted by the moderator analysis in our paper. In areas with a lower resilience level, one possible policy that local governments want to consider is the voucher program, which sent out vouchers to local residents for restaurant consumption, and restaurants can use the collected vouchers to pay for government taxes. Second, from a long-run perspective, the restaurant industry can devise strategic plans to improve its resilience to pandemics. Based on our results, restaurants can devote more attention to nurturing the takeout and delivery market. Also, restaurants in densely populated areas should consider more effective measures to protect customers, such as minimizing direct human interaction, providing sanitizing products, offering single-use items (e.g., menus and condiments), and digitalizing transactions (e.g., check-in/-out).

(Please insert Figure 4 about here)

Our estimated models can also aid the industry from a data-analytic perspective. The demand loss model estimated in this paper can be used for demand forecasting and scenario simulation. For example, as pandemic forecasts are developed via epidemiological models, we can predict restaurant demand based on a set of parameters. More accurate demand forecasting will enable businesses to allocate their resources more efficiently and prepare for surging demand. Moreover, our model can be used as a simulator to understand the effects of policy alteration. For instance, when confronted with diverse policy/regulation changes (e.g., in stay-at-home orders and restaurant business restrictions), the industry can better simulate possible scenarios to explore potential outcomes of government proposals. Interestingly, we noticed limited empirical attempts in the literature to quantify different weather determinants on restaurant demand, and our calibrated models provide insight into how to rigorously estimate restaurant demand based on weather forecasts.

Some limitations may compromise the generalizability of our results. First, we measured restaurant demand using two big data sources, and potential measurement errors in these data could influence the reliability of our conclusions. Second, we did not use data from individual restaurants. Aggregate county-level data may be subject to potential aggregation bias and fail to reflect the heterogeneity of individual restaurants, such as demand associated with particular locations and chain affiliations. After all, given a current push to revive the economy despite uncertainty in how the pandemic will continue to unfold, it remains to be seen whether customers will have the confidence to begin visiting restaurants and restore a sense of normalcy when dining out. Under this tenuous economic environment, empirical studies investigating restaurant businesses' responses throughout the pandemic will be particularly valuable. We are calling for further analysis based on primary survey data to shed light on restaurant customers' behavior change in response to COVID-19 pandemics. Third, we used data from the U.S., hence whether the findings are generalizable to other countries needs further testing. It would be interesting to test the proposed relationships in an Asian country and compare the results from the East and the West, as Asian countries have significantly different socio-economic characteristics, pandemic management practices and policies, cultural habits as well as attitudes toward the government and the pandemic among consumers compared to their Western counterparts.

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Table 1. Descriptive statistics of variables

Variable	Obs	Mean	Std. Dev.	Min	Max	VIF
ln*visits*	113,357	10.303	1.076	8.169	15.507	
ln*visits_fast_food*	54,539	9.906	0.759	7.992	13.862	
ln*transaction*	107,437	8.262	1.370	0.409	13.730	
ln*new_cases*	113,357	0.546	1.149	0.000	7.693	1.67
stay_at_home	113,357	0.278	0.448	0.000	1.000	2.66
ln*sum_rainfall*	113,357	3.288	3.497	0.000	12.869	1.01
temperature	113,357	48.142	15.901	-14.350	103.730	1.01
temperature2	113,357	2570.470	1601.988	0.002	10759.910	
rest_restriction	113,357	0.372	0.483	0.000	1.000	2.51
ln*density*	113,357	5.046	1.311	0.405	11.180	
ln*family_size*	113,357	1.107	0.065	0.871	1.389	
ln*tourism*	113,357	-5.760	1.115	-10.869	-0.236	
eat_in	113,357	0.424	0.005	0.405	0.445	

Table 2. Estimation results of baseline models with foot-traffic data.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
	lnvisits	lnvisits	lnvisits	lnvisits_fast_food	lnvisits_fast_food	lnvisits_fast_food
ln*new_cases*	-0.0567***		-0.0556***	-0.0312***		-0.0296***
	(0.003)		(0.003)	(0.003)		(0.003)
stay_at_home		-0.0602***	-0.0330***		-0.0676***	-0.0487***
		(0.009)	(0.009)		(0.009)	(0.009)
ln*sum_rainfall*	-0.00444***	-0.00486***	-0.00437***	-0.00339***	-0.00361***	-0.00331***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
temperature	0.00204***	0.00282***	0.00208***	0.00340***	0.00380***	0.00346***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
temperature2	-0.00000800	-0.0000141**	-0.00000907*	-0.0000214***	-0.0000247***	-0.0000229***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
rest_restriction	-0.0588***	-0.0686***	-0.0608***	0.000169	-0.00688	-0.00291
	(0.011)	(0.011)	(0.011)	(0.008)	(0.009)	(0.009)
constant	10.52***	10.50***	10.52***	9.972***	9.962***	9.973***
	(0.011)	(0.012)	(0.011)	(0.010)	(0.011)	(0.010)
Day-specific effects	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
N	113357	113880	113357	54718	54946	54718
R-sq	0.599	0.574	0.600	0.501	0.489	0.503
Counties	1882	1882	1882	1032	1032	1032

(Notes:)

Table 3. Estimation results of models with moderating variables

	Model 7	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**	**Model 13**	**Model 14**
	lnvisits	lnvisits	lnvisits	lnvisits	lnvisits	lnvisits	lnvisits	lnvisits
ln*new_cases*	0.0225	-0.0275***	-0.0935**	-0.0548***	-0.245***	-0.0530***	-0.399**	-0.0556***
	(0.015)	(0.003)	(0.040)	(0.003)	(0.015)	(0.003)	(0.201)	(0.003)
stay_at_home	-0.0295***	0.328***	-0.0332***	0.0348	-0.0387***	-0.520***	-0.0335***	-0.0541
	(0.009)	(0.028)	(0.008)	(0.103)	(0.008)	(0.033)	(0.009)	(0.412)
ln*new_caseslndensity**	-0.0114***							
	(0.002)							
***stay_at_home**lndensity**		-0.0691***						
		(0.005)						
ln*new_casesln*family_size***			0.0326					
			(0.035)					
stay_at_home**ln*family_size				-0.0610				
				(0.092)				
ln*new_caseslntourism**					-0.0336***			
					(0.003)			
***stay_at_home**lntourism**						-0.0844***		
						(0.006)		
ln*new_cases*eat_in***							0.806	
							(0.490)	
stay_at_homeeat_in***								0.0496
								(0.968)
ln*sum_rainfall*	-0.00427***	-0.00418***	-0.00437***	-0.00438***	-0.00440***	-0.00435***	-0.00440***	-0.00437***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
temperature	0.00202***	0.00178***	0.00210***	0.00204***	0.00186***	0.00194***	0.00203***	0.00208***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)

temperature2	-0.00000866*	-0.00000704	-0.00000925*	-0.00000871*	-0.00000695	-0.00000798*	-0.00000848	-0.00000905*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
rest_restriction	-0.0604***	-0.0634***	-0.0608***	-0.0607***	-0.0605***	-0.0590***	-0.0608***	-0.0608***
	(0.011)	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)
constant	10.52***	10.52***	10.52***	10.52***	10.52***	10.52***	10.52***	10.52***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)
Day-specific effects	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
N	113357	113357	113357	113357	113357	113357	113357	113357
R-sq	0.604	0.615	0.600	0.600	0.616	0.623	0.600	0.600
Counties	1882	1882	1882	1882	1882	1882	1882	1882

Table 4. Robustness check using transaction data as dependent variable.

	Model 15	**Model 16**	**Model 17**	**Model 18**	**Model 19**	**Model 20**	**Model 21**	**Model 22**	**Model 23**
	lntransaction	lntransaction	lntransaction	lntransaction	lntransaction	lntransaction	lntransaction	lntransaction	lntransaction
ln*new_cases*	-0.0209*** (0.002)	0.000868 (0.008)	-0.0179*** (0.002)	0.00842 (0.025)	-0.0208*** (0.002)	-0.0549*** (0.010)	-0.0202*** (0.002)	0.910*** (0.110)	-0.0183*** (0.002)
stay_at_home	-0.0421*** (0.005)	-0.0413*** (0.005)	-0.00491 (0.017)	-0.0419*** (0.005)	-0.0269 (0.055)	-0.0429*** (0.005)	-0.142*** (0.021)	-0.0407*** (0.005)	2.153*** (0.270)
ln*new_caseslndensity**		-0.00314** (0.001)							
***stay_at_home**lndensity**			-0.00717** (0.003)						
ln*new_casesln*family_size***				-0.0253 (0.022)					
stay_at_home**ln*family_size					-0.0137 (0.049)				
ln*new_caseslntourism**						-0.00605*** (0.002)			
***stay_at_home**lntourism**							-0.0173*** (0.003)		
ln*new_cases*eat_in***								-2.183*** (0.258)	
stay_at_homeeat_in***									-5.167*** (0.635)

ln*sum_rainfall*	-0.000857***	-0.000838***	-0.000848***	-0.000852***	-0.000856***	-0.000854***	-0.000837***	-0.000808***	-0.000786***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
temperature	-0.000571*	-0.000576*	-0.000593*	-0.000577*	-0.000577*	-0.000598*	-0.000590*	-0.000458	-0.000447
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
temperature2	0.0000177***	0.0000178***	0.0000180***	0.0000177***	0.0000178***	0.0000179***	0.0000177***	0.0000164***	0.0000164***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
rest_restriction	-0.0767***	-0.0767***	-0.0771***	-0.0768***	-0.0767***	-0.0766***	-0.0763***	-0.0766***	-0.0770***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
constant	8.379***	8.379***	8.379***	8.379***	8.379***	8.380***	8.380***	8.377***	8.376***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Day-specific effect	Controlled			Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
N	107437	107437	107437	107437	107437	107437	107437	107437	107437
R-sq	0.664	0.664	0.664	0.664	0.664	0.665	0.665	0.666	0.666
Counties	1982	1982	1982	1982	1982	1982	1982	1982	1982

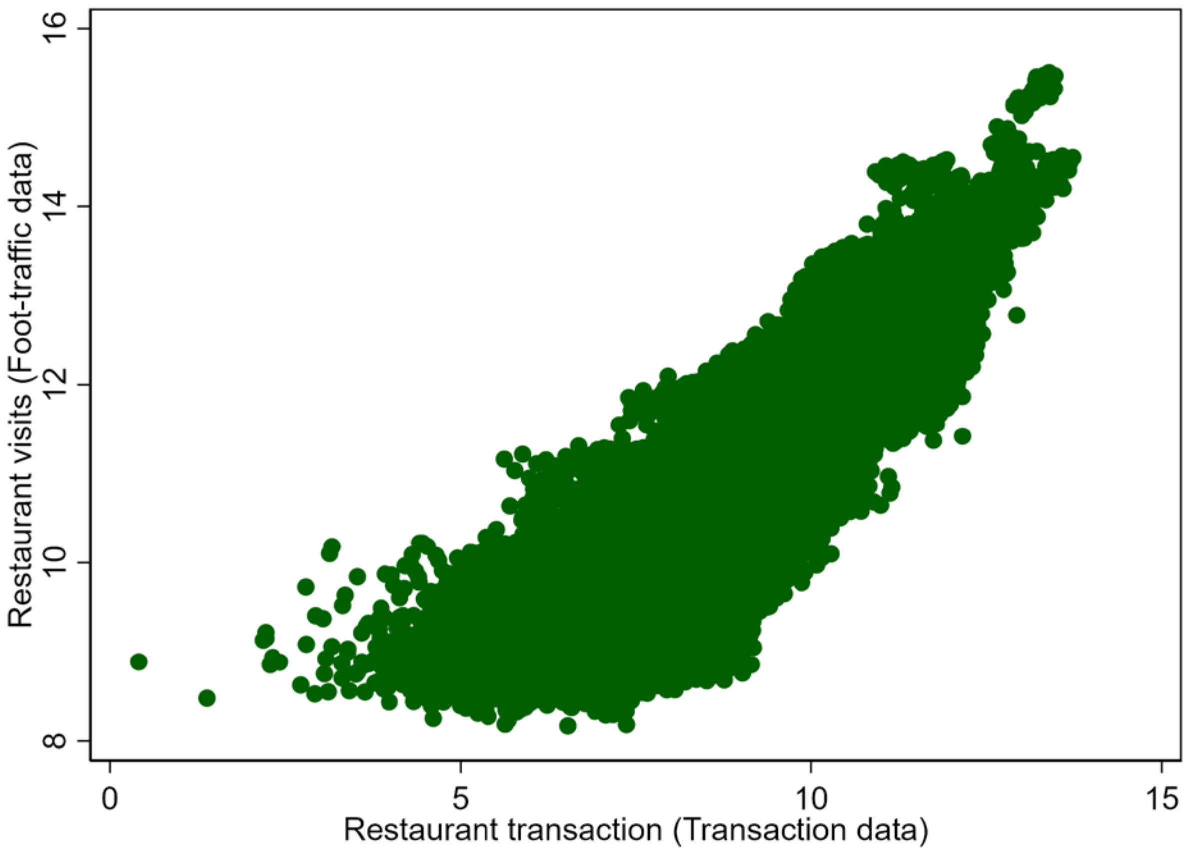

Figure 1. Scatter plot of restaurant visit from foot traffic data and transcation amount from transaction data.

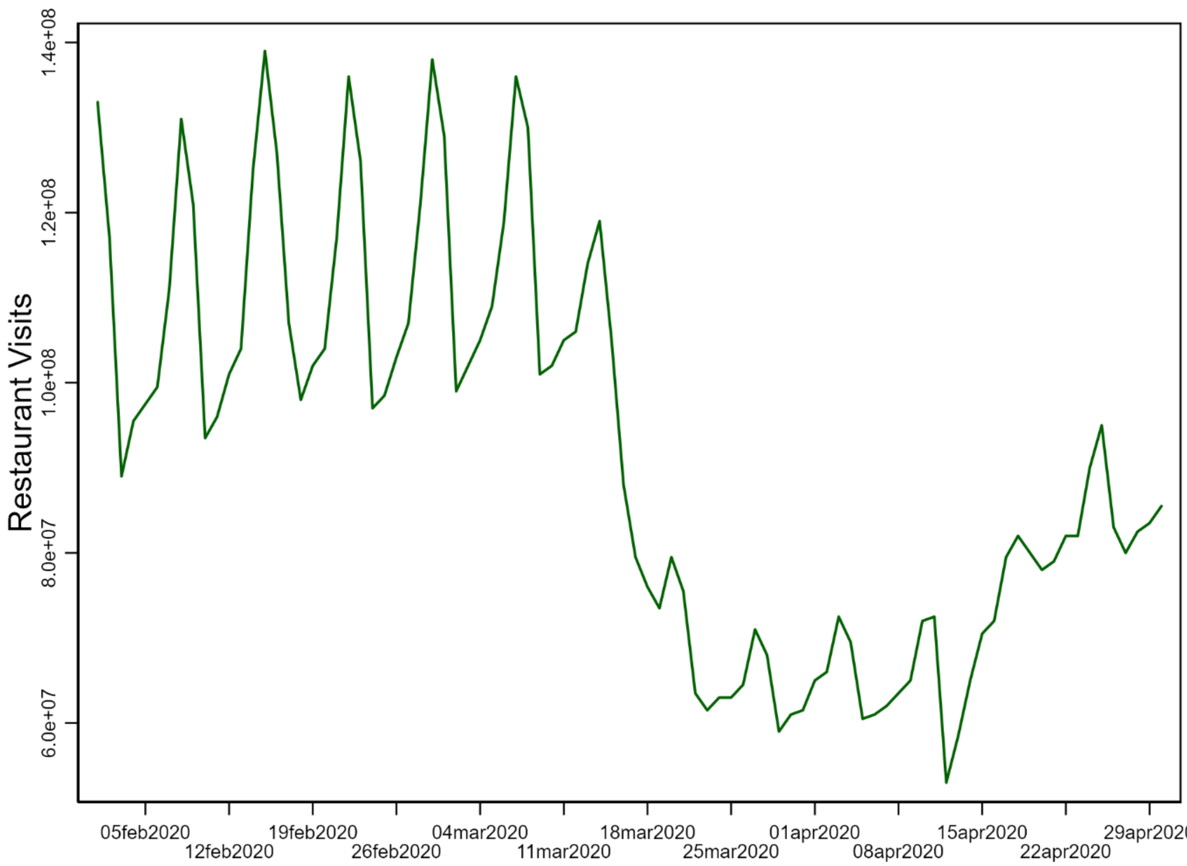

Figure 2. Change in restaurant visits over time.

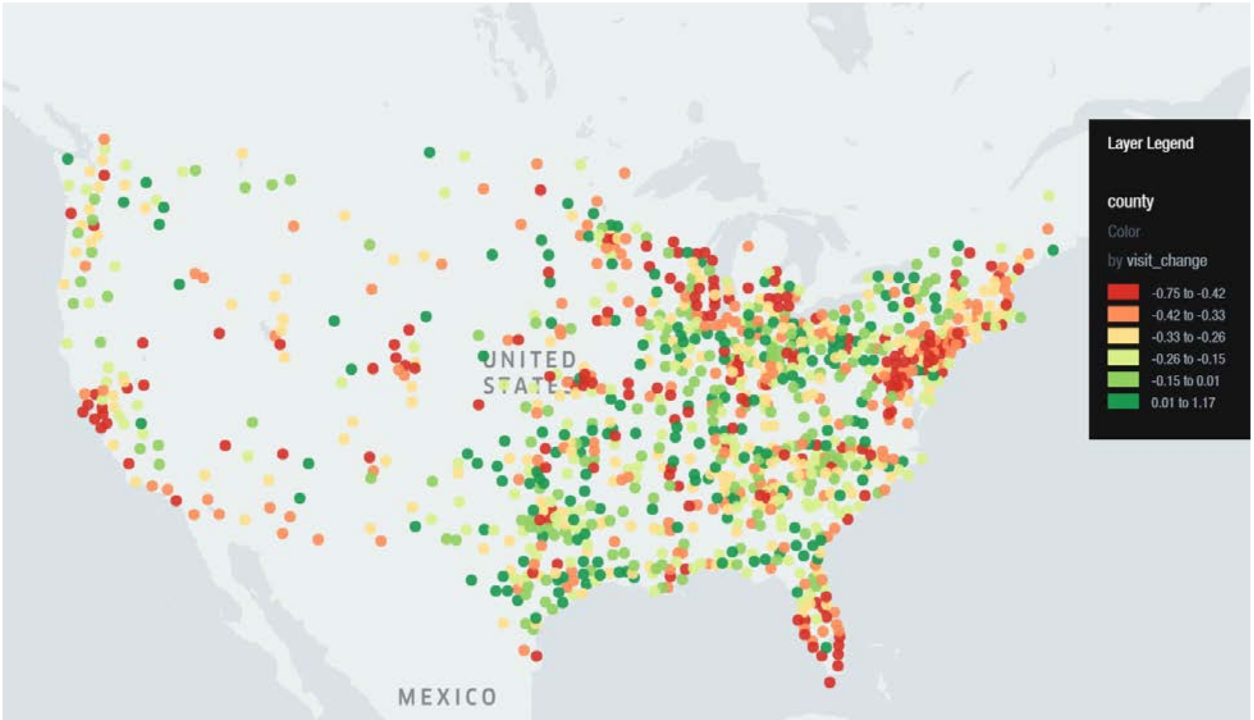

Figure 3. Change in restaurant visits from Feb 1 to April 30 in each U.S. county (contiguous states only).

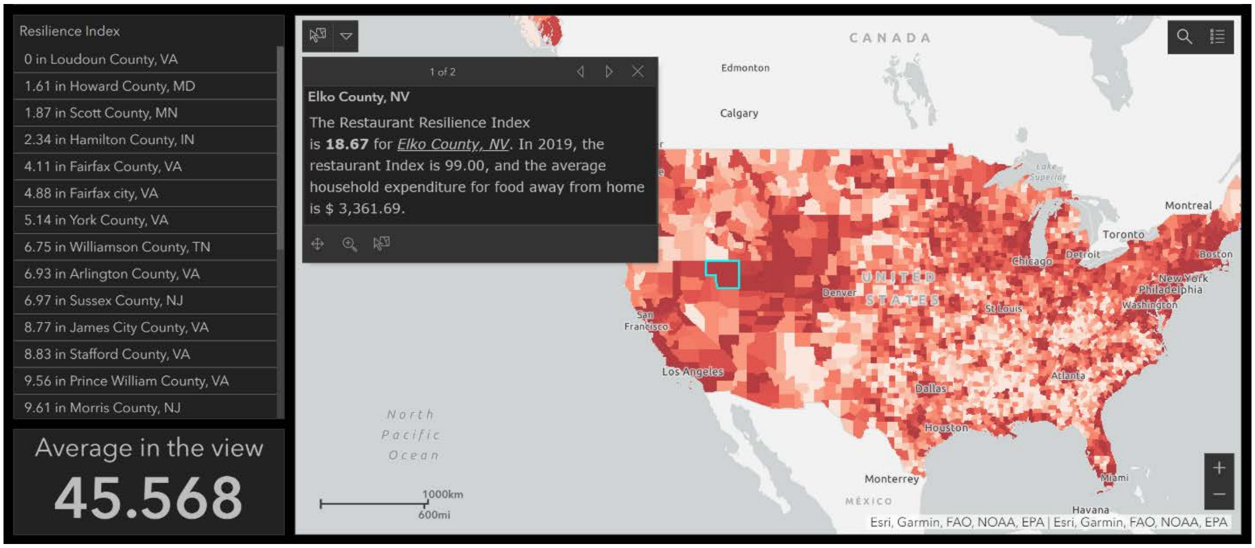

Figure 4. Restaurant resilience index based on econometric modeling.