

## RESEARCH ARTICLE

# Public responses to COVID-19 case disclosure and their spatial implications

Kwan Ok Lee<sup>1</sup>  | Hyojung Lee<sup>2</sup> 

<sup>1</sup>NUS Business School, National University of Singapore, Singapore, Singapore

<sup>2</sup>Department of Apparel, Housing, and Resource Management, Virginia Polytechnic Institute and State University, Blacksburg, Virginia, USA

## Correspondence

Kwan Ok Lee, NUS Business School, National University of Singapore, 15 Kent Ridge Drive Mochtar Riady Building #07-51, Singapore 119245, Singapore.  
Email: [kwan.lee@nus.edu.sg](mailto:kwan.lee@nus.edu.sg)

## Funding information

Singapore Ministry of Education AcRF Tier 1 fund; National University of Singapore, Grant/Award Number: R-297-000-146-115

## Abstract

We study how the public changes their mobility and retail spending patterns as precautionary responses to the disclosed location of COVID-19 cases. To look into the underlying mechanisms, we investigate how such change varies spatially and whether there is any spatial spillover or substitution. We use the daily data of cell phone-based mobility and credit card transactions between February 10 and May 31 in both 2019 and 2020 in Seoul, South Korea, and employ the empirical approach analyzing the year-over-year percent change for the mobility and consumption outcomes. Results report that one additional COVID-19 case within the last 14 days decreased nonresident inflow and retail spending by 0.40 and 0.65 percentage points, respectively. Then, we also find evidence of spatial heterogeneity: the mobility and retail performances of neighborhoods with higher residential population density were more resilient to COVID-19 case information while neighborhoods with higher levels of land-use diversity and retail agglomeration experienced a greater localized demand shock. This heterogeneity is not negligible. For example, one additional COVID-19 case in neighborhoods in the bottom 20% for population density led to a decline of 1.2 percentage points in retail spending, while other neighborhoods experienced a less negative impact. Finally,

This is an open access article under the terms of the Creative Commons Attribution-NonCommercial-NoDerivs License, which permits use and distribution in any medium, provided the original work is properly cited, the use is non-commercial and no modifications or adaptations are made.

© 2021 The Authors. *Journal of Regional Science* published by Wiley Periodicals LLC

we find a significant spatial spillover effect of disclosed COVID-19 information instead of spatial substitution. One additional COVID-19 case in geographically adjacent areas within the last 14 days reduced nonresident inflow and retail spending in the subject neighborhood by 0.06 and 0.09 percentage points, respectively.

**KEYWORDS**

COVID-19, location disclosure, neighborhood spillover, precautionary behavior, spatial heterogeneity

## 1 | INTRODUCTION

During the COVID-19 pandemic, a handful of countries and economies mainly in Asia, including South Korea, Hong Kong, and Singapore, chose to disclose detailed location information of the residence and visiting places of individuals who tested positive, along with mass testing and contact tracing. While this strategy is expected to be useful to promote voluntary precautionary behavior and combat the virus's spread, such behavior can also lead to significant economic impacts in some local areas. If the public is informed that there is a potentially higher health risk in a certain neighborhood, this risk should be reflected in the individual choice to visit and/or engage in retail or leisure activities in this neighborhood.

The purpose of this paper is to provide empirical evidence on how the public changed their mobility and retail spending patterns as precautionary responses to the disclosed location of COVID-19 cases in Seoul, South Korea. Our main research question is on the extent to which disclosed COVID-19 cases in a given neighborhood led to the reduction in nonresident inflows to and retail spending in that neighborhood. Hence, we focus on neighborhood-level spatial implications of COVID-19 case disclosure. To look into underlying mechanisms, we investigate whether spatial attributes such as population/employment density, land-use diversity, and the level of retail agglomeration play a role in the neighborhood's resilience to demand shock. We also examine whether increasing COVID-19 risks in geographically or functionally adjacent neighborhoods increase or decrease mobility and retail spending in a subject neighborhood.

To do so, we utilize big data and a carefully designed empirical framework. Two big data sources we use include cell phone-based mobility and credit card spending between February 10 and May 31 in both 2019 and 2020. They are provided by companies that have a large market share in their respective sectors in South Korea. More importantly, both data are available at a relatively smaller geographic level, called "dong" (hereafter, neighborhood), and on a daily frequency. Therefore, our data provide a fairly complete and accurate picture of neighborhood-level demand changes at high frequency, allowing us to conduct comprehensive empirical analyses. We use the first-difference type of empirical models by calculating the year-over-year percent change for two outcome variables: nonresident inflow to and retail spending in a given neighborhood. As COVID-19 has significantly affected these outcomes in a short period, it is important to track down how they have changed during COVID-19 compared with the prepandemic period.

We find that the disclosure of COVID-19 cases led to localized demand shock as both nonresident inflow and retail spending decreased significantly in neighborhoods with more cases. Estimation results report that one additional COVID-19 case during the last 14 days decreased nonresident inflow and retail spending by 0.40 and 0.65 percentage points, respectively. Our results are consistent with Janssen and Shapiro (2020), who find a significant reduction in the probability of individuals to visit the subregion with more cases disclosed 1 day before in Singapore.



They find that an additional resident and visitor case decreases the individual's probability of visiting the subregion by 0.081 and 0.017 percentage points, respectively. While results from two studies are not directly comparable due to different empirical approaches and local contexts, we believe that the magnitude of our results is larger because we use a lot smaller geographic areas and the cumulative number of cases.

Our results on retail spending reduction as responses to disclosed COVID-19 case are consistent with Chetty et al. (2020), who report a significant reduction in credit and debit card spending in the United States. Their result suggests that the average daily spending in food services in March and April 2020 decreased by 25–50 percentage points relative to January 2020 spending while the reduction in total retail spending is less fluctuating. This coincides with our result that the greatest reduction effects are found in retail credit card spending. However, the magnitude of the reduction in retail spending shown in Chetty et al. (2020) is not comparable to ours because our focus is not the nationally aggregated reduction in credit card spending after the COVID-19 pandemic but the neighborhood-level reduction responding to an additional case in the neighborhood.

In terms of spatial heterogeneity in the demand shock that we consider as underlying mechanisms of the impact of COVID-19 case disclosure, our analysis focuses on neighborhood population density, land use, and the level of retail agglomeration. Resident population density and employment density are found to play different roles. On the one hand, mobility and retail performances of neighborhoods with lower resident population density were more affected by COVID-19 incidences compared with those with higher population density. On the other hand, neighborhoods with different levels of employment density show much less heterogeneous results. In addition, the higher levels of land-use diversity and retail agglomeration reduced localized economic resilience to the COVID-19 case shock potentially due to public concerns about the virus's spread. Finally, we test whether there is a spatial spillover or substitution effect of disclosed COVID-19 case information and find that the spillover effects dominate: an increase in COVID-19 risks in both geographically and functionally adjacent neighborhoods reduced nonresident inflow and retail spending in the subject neighborhood.

The remainder of the paper is organized as follows. Section 2 presents scholarly contributions of our paper to the relevant literature as well as the institutional backgrounds of the location disclosure of COVID-19 cases in Seoul, South Korea. Section 3 describes the data and summary statistics while Section 4 presents empirical strategies and identification. Section 5 discusses results from baseline regressions and spatial analyses and Section 6 concludes this study.

## 2 | BACKGROUNDS

### 2.1 | Scholarly background

One strand of the research relevant to our paper is the literature on economic outcomes of the pandemic. Many scholars have focused on how COVID-19 affected household consumption (e.g., Baker et al., 2020; Carvalho et al., 2020; H. Chen et al., 2021; Chetty et al., 2020; Coibion et al., 2020; Surico et al., 2020), labor market outcomes (e.g., Béland et al., 2020; Bernstein et al., 2020; Chetty et al., 2020; Gupta et al., 2020; Kahn et al., 2020; Marcén & Morales, 2021; Rojas et al., 2020), and health (e.g., Fetzner et al., 2021; Hamermesh, 2020; Kosfeld et al., 2021; Lu et al., 2020). Others studied public behavioral responses to different social-distancing policies (Abouk & Heydari, 2021; Allcott et al., 2020; Brough et al., 2021; Courtemanche et al., 2020; Dave et al., 2020; Farboodi et al., 2020; Nguyen et al., 2020; Siedner et al., 2020). These studies use cell phone mobility data in the United States and their main goal is to evaluate policy effectiveness on the reduction in virus spread. These studies offer useful insights on a change in general travel behaviors during the pandemic. In particular, the finding of Dave et al. (2020) on the increasing net stay-at-home behavior caused by Black Lives Matter protests could be understood as similar precautionary responses to what we find with the increasing number of disclosed COVID-19 cases in Seoul. However, none of these studies provides spatial implications. Also, as governments in the United States have not released the

detailed location information of COVID-19 cases, findings tend to remain at the macrolevel. For example, Andersen (2020) and Painter and Qiu (2020) consider the variation in the extent of social-distancing behaviors at the county and state levels, respectively. Our research adds insights on localized responses to the disclosed COVID-19 case information and associated behavioral and economic outcomes in different neighborhoods within a city.

Argente et al. (2020) and Janssen and Shapiro (2020) are among few examples that analyze mobility outcomes of disclosed location information of COVID-19 cases in the contexts of Seoul and Singapore, respectively.<sup>1</sup> However, their outcomes of interest differ from ours. Argente et al. (2020) are interested in the virus's spread and model it to be related with commuting flows. They use an SIR meta-population model to compare the reduction in COVID-19 infections and deaths in the context of the information disclosure policy with counterfactual outcomes of a policy without such disclosure and a lockdown policy. Utilizing device-level cell phone data in Singapore, Janssen and Shapiro (2020) analyze how disclosed local cases in the subregion of the individual's residence leads to a change in individual travel behavior. They also look into the extent to which COVID-19 cases in a given subregion influence the inflow of individuals. As this is partially similar to our first research question associated with non-resident inflows, we aim to test the external validity of results and compare findings. Unlike Janssen and Shapiro (2020), however, our study goes beyond the travel-related precautionary behavior because our main focus is on localized economic shock observed with both nonresidential inflows and retail spending. Moreover, our spatial unit of analysis is a lot more refined at 424 neighborhoods compared with 25 districts in Argente et al. (2020) and 55 subregions in Janssen and Shapiro (2020).

Next, our research intends to provide a better understanding of the literature on the role of spatial attributes to pandemic outcomes. While it is known that it is more challenging to control epidemics in higher density areas (Wamsler et al., 2013; Wheaton & Kinsella Thompson, 2020), there is little consistent evidence on how areas with different levels of density have survived and recovered during and after the pandemic. Stevens et al. (2010) and Malalgoda et al. (2013) report that higher density is associated with both higher risks and slower recovery from natural disasters. In contrast, Capello et al. (2015) suggest the lower loss of GDP growth in regions with cities with a larger population during the economic crisis in Europe, potentially due to agglomeration benefits. Although the COVID-19 pandemic is an inherently different shock from natural disasters and economic recession due to no physical destruction and concerns about the virus's spread, these studies offer some motivation. Land-use diversity is another spatial attribute that could be associated with pandemic outcomes. Researchers tend to find negative effects of nonresidential land-use components on COVID-19 incidences. Wheaton and Kinsella Thompson (2020) report a positive impact of commercial-industrial land-use share on cases in Massachusetts. Y. Chen et al. (2020) similarly show the correlation between green space density and cases in New York City.

Finally, our study is relevant to the literature on the role of spatial patterns in retail resilience. One popular strategy used to enhance this resilience is retail agglomeration.<sup>2</sup> Nonetheless, there is little empirical evidence on whether retail agglomeration did enhance retail resilience during and after natural or economic shocks. Meltzer et al. (2020) report that retail businesses serving localized consumer bases and smaller and standalone establishments have been affected most by Hurricane Sandy in New York. Wrigley and Dolega (2011) suggest a higher resilience of retail centers with diversity and corporate-food-store entry during a global economic crisis in towns in the United Kingdom. Both studies focus on store-level analysis rather than spatial implications. Again at the store level, and in the context of the COVID-19 pandemic, Tucker and Yu (2020) find no demand substitution between restaurant types while reporting that restaurant chains suffer a smaller decrease in visits. This study adds to existing evidence by observing how neighborhoods with a different level of retail agglomeration survive from localized demand shocks during COVID-19.

<sup>1</sup>Xie and Micheva (2020) look into the effect of disclosed cases on the returns of real estate firms in Hong Kong. The outcome of this study is financial decisions of a relatively small number of citizens so it is less relevant to general public responses.

<sup>2</sup>For example, shopping streets or centers could achieve a higher market share by minimizing the location differentiation toward customers and satisfy consumer preference by reducing their effort to compare and purchase goods (Brown, 1989; Nelson, 1958; Reimers & Clulow, 2004).

## 2.2 | Institutional background

South Korea is one of few countries that have never imposed a compulsory lockdown, although it went through quite early outbreaks of COVID-19 starting from January 20, 2020. Also, most corporations in South Korea did not make working from home mandatory. This means that people in South Korea carried out their daily commuting at a similar level as the pre-COVID period and chose other activities simply based on their voluntary precaution. This is an important precursor of our analysis because individual demand to visit and shop in local neighborhoods is not limited by any other measures than disclosed location information of COVID-19 cases. The South Korean government did impose different levels of social-distancing measures since March as a policy response to increasing or decreasing numbers of COVID-19 cases. For example, for 1 month from March 22, the operation of religious places, entertainment businesses such as clubs, and some indoor sports facilities was restricted fully or partially. This falls in our study period of February 10–May 31, 2020. However, the level of social distancing has been kept consistent for the entire city of Seoul, which is our study area. As there is no spatial variation in this level, COVID-19 case effects would not be confounded with the impacts of social distancing. And any temporal change in the social-distancing level should be captured by date fixed effects.

To promote voluntary precautionary behaviors, government bodies in South Korea, including district offices, the Seoul Metropolitan Government, and Korea Disease Control and Prevention Agency, have actively provided location details about each COVID-19 case after epidemiologic investigation. For example, district offices in Seoul send text messages for every positive COVID-19 case to all cell phone users located within the same district as the case's residence.<sup>3,4</sup> The text is also sent to request the public to report and get a test if they visited the same place the confirmed COVID-19 case visited in a given district or sometimes in Seoul. This is to identify close contacts of a case and essentially disclose the locations with higher risks. Besides these involuntary text messages, South Korean government bodies widely disseminate the information on the details of the case's residence and visiting places on their websites. Individuals could also use the mobile phone application to follow COVID-19 case information in any districts of their interest.

## 3 | DATA AND DESCRIPTIVE STATISTICS

This study uses data from several sources. The first is based on the publicly released information on COVID-19 cases for the period of February–May 2020. As mentioned in Section 2, this information is from various online platforms. As it is provided in the pure text format, we manually coded it for 862 cases reported in Seoul.

<sup>3</sup>The text message is sent to anyone located within the range of the base stations in the district of the case's residence at the time of the message transmission. The message briefs the residence of the COVID-19 case and provides a web link (usually on the district website or blog) for more details of the case. The link discloses the age and gender of the COVID-19 patient as well as all locations that the patient visited with the timeline in the past week.

<sup>4</sup>An example of the urgent disaster text is as follows:

- Gangnam gu office] one new case (total 27). For details, refer to the homepage ([www.gangnam.go.kr](http://www.gangnam.go.kr)).

An example of the district homepage information is as follows:

- #27 case (2020-03-26): 25 years old male, resident in Gaepo-dong.
- March 22: 16:00 Arrived at Incheon International Airport.  
19:20 Visited a restaurant in Yeoksam-dong (with a map attached) (disinfection scheduled, investigating close contacts) 20:00 Came home (disinfection completed, two family members in contact ordered to serve self-quarantine);
- March 23: Visited the father's home in Jeonju-si.
- March 23: 13:00 Came home (disinfection completed).  
15:00 Visited a convenience store in Gaepo-dong;
- March 25: Visited Gangnam-gu health office COVI-19 test.
- March 26: Positive test results.

Our final data are arranged to generate explanatory variables for our analyses at the neighborhood “dong” level,<sup>5</sup> the smallest administrative area in Seoul: the number of residents confirmed as having tested positive for COVID-19 in each neighborhood within the last 14 days, the number of visits by the confirmed patients to the neighborhood within the last 14 days, and the sum of these two numbers.<sup>6</sup> If the patient visits the places in the same neighborhood of his or her residence, we do not add this to the number of visitors in this neighborhood to prevent duplicate counts.<sup>7</sup>

Second, we use two proprietary data to analyze outcomes of the disclosed location information of COVID-19 cases. The cell phone-based daily mobility data were provided by SK Telecom.<sup>8</sup> SK Telecom is the largest mobile phone company in South Korea, accounting for a market share of about 42%.<sup>9</sup> The data provide daily bilateral flows of people between their residence and destination neighborhood, where they stayed more than 30 min (to exclude movements through car and/or public transportation). The data cover the time period of February 10–May 31 in both 2019 and 2020,<sup>10</sup> which enables us to observe differences in mobility in a neighborhood in a given day, adjusting for the day of week, between 2019 and 2020. The main variable we generate for the analysis is the daily year-over-year percent change in nonresident inflows reflecting the baseline inflow in each neighborhood.

Then, we measure consumption behaviors in neighborhoods within Seoul by using the credit card transaction data from Hyundai Card, which has about 16% of the market share in South Korea.<sup>11</sup> Like the cell phone data, credit card data cover the time period of February–May of 2019 and 2020. In addition to the total sales amount, daily sales are reported by industry, which allows us to identify consumption across major consumption categories. Here, we focus on consumption in the retail sector, which includes “retail trade,” “tourism, entertainment, and recreation,” and “food services.” The main variables we generate for the analysis are the daily year-over-year percent change in total credit card spending and the change in retail spending in each neighborhood.

While analyzing the impact of the public disclosure of COVID-19 cases on mobility and consumption in Seoul can provide valuable insights, the averaged estimates may disguise spatial heterogeneity across areas with different characteristics within the city. To explore this as underlying mechanisms for our analysis, we sort all neighborhoods in Seoul into quintiles by the rank of population density, employment density, Theil entropy score of land-use diversity, and retail agglomeration. The population and employment density data were obtained from Seoul Open Data Plaza, which is a platform where the Seoul Metropolitan Government provides its public data. The Theil entropy score was computed by aggregating total floor area by building use type (e.g., residential, commercial, industrial, and office) at the neighborhood level, based on the building-level geographic information system (GIS)

<sup>5</sup>Neighborhood units in South Korea are called *dong* in urban areas. These are the smallest geographic levels defined administratively in South Korea, and their median population size is approximately 5000, similar to that of census tracts in the United States. In this study, we define *dong* as neighborhoods and use the neighborhood fixed effects for all analyses.

<sup>6</sup>Since public information acquisition is a key mechanism for our analysis, we use the disclosure date of case information when compiling these numbers. We use the horizon of 14 days as demand shock tends to last for 14 days from the disclosure date (Table 3 and Appendix A). In alternative specifications, we use the number of cases within the last 7 days, and the results (available upon request) appear to be consistent.

<sup>7</sup>For example, the case shown in Footnote 4 is recorded as a resident case for the neighborhood Gaepo-dong while he is not recorded as a visit case for this neighborhood even though he visited a convenience store within the neighborhood. As he visited a restaurant, he is recorded as a visit case in Yeoksam-dong.

<sup>8</sup>Argente et al. (2020) use the similar data while their geographic level is larger than ours.

<sup>9</sup>The SK Telecom data we obtained was weighted for age, sex, and regions to construct representative estimates.

<sup>10</sup>In 2020, January had many holidays (5 days) compared with no holidays in February and March in South Korea. In particular, there were four consecutive holidays for Lunar New Year in January 2020 while the same holidays fell in early February for 2019. Since many people leave Seoul during these holidays, year-over-year change in daily mobility within Seoul appears to be fluctuating a lot. As this could potentially influence our mobility analysis, we decided our main sample period to be February 10–May 31. Another advantage of using this sample is to account for the fact that most measures to promote precautionary behavior with location disclosure of the COVID-19 cases (e.g., text messages) began after early February. We use the sample of January 1–May 31 for our robustness check and results remain consistent.

<sup>11</sup>Most credit cards in South Korea are either Visa or MasterCard and different companies including Hyundai issue these cards. The way that these companies attract customers and issue cards to them are quite similar, so we do not believe that there is a systematic difference in socioeconomic characteristics for consumers in our sample compared with other credit card users in South Korea.

data constructed and provided by the Ministry of Land, Infrastructure and Transport of South Korea.<sup>12</sup> Lastly, for retail agglomeration, we use neighborhood's share of credit card spending in the retail sector in Seoul based on Hyundai Card transaction data in 2015–2019 (prepandemic period).

Table 1 presents descriptive statistics of main variables. On average, there are more visitor cases than resident cases. The average number of cases in the previous 14 days is 0.533 per neighborhood. One may be surprised at how these few cases could have generated a change in public behavior in a large city like Seoul. We note that public fear was very strong, especially at the beginning of the pandemic. In fact, because the number of cases was not very high compared with other cities, the public may have been more sensitive to the location information of one additional case. This is exactly why the government used the location disclosure of cases rather than the lockdown policy as the main measure to combat the spread of COVID-19. There is evidence that public responses driven by this measure were significant enough to maintain the number of cases low in Seoul (Argente et al., 2020). In addition, a standard deviation is quite large for COVID-19 cases (Table 1), and this may have led to a significant variation in outcomes between neighborhoods. On the other hand, on average, there is a larger reduction in mobility than spending. However, a standard deviation is much larger for spending, especially spending in the retail sector, indicating that while most neighborhoods experience a relatively similar reduction in foot traffic, retail sectors in certain neighborhoods are more vulnerable than others.

As shown in Figure 1, the public in Seoul has actively responded to the case information disclosure by reducing their daily mobility and credit card spending.<sup>13</sup> The average year-over-year mobility declined up to 26% from February to May 2020 (Panel A, Figure 1). Especially when the disclosed number of cases reached its peak in early March, we see a significant drop in mobility followed by a slow recovery over time.<sup>14</sup> The average year-over-year credit card spending also declined up to 62% from February to May 2020 (Panel A, Figure 1) although this shows more fluctuation than the daily mobility trend. This is comparable to An et al. (2021) reporting that the average year-over-year reduction in US ZIP code-level credit card spending in April 2020 is 25% and the 75th percentile is 38%.

When we focus on the local level, however, the degrees of reduction in daily mobility and credit card spending varies significantly (Panel B, Figure 1). While some areas, including the three major central business districts (CBDs) in Seoul and transportation hub areas with airport, bus terminal, and train station, experienced more than a 20% reduction in nonresident inflow and retail spending compared with 2019, others saw a lot less reduction or even a slight increase in local economic activities. While this spatial heterogeneity would be somewhat related to the distribution of disclosed cases, no direct association is observed (Panel C, Figure 1). This case distribution in Seoul appears to be less heterogeneous compared with the distribution of economic outcomes.

## 4 | EMPIRICAL STRATEGY AND IDENTIFICATION

Although the COVID-19 outbreak is a seemingly exogenous shock, we should still be concerned about the presence of other concurrent shocks to neighborhoods and households within Seoul. To overcome such an identification challenge, most existing research on the outcomes of the COVID-19 pandemic uses either the difference-in-difference approach

<sup>12</sup>We compute the Theil entropy score to measure the level of land-use diversity in a given neighborhood. Analogous to the entropy score that measures a neighborhood's racial or ethnic diversity, we measure the diversity of building uses within a neighborhood following the formula suggested by Massey and Denton (1988):  $E = -\sum(\pi_r)\ln[1/\pi_r]$ , where  $\pi_r$  represents the proportion of the building floor area in building use  $r$ , and the entropy score  $E$  is calculated for each neighborhood. Here, the entropy score will be maximized if building types are evenly distributed, and thus the higher the entropy score, the greater the land-use diversity a neighborhood has.

<sup>13</sup>We find some lagged responses. Also, a positive correlation is found between the number of cases and credit card spending at some points and this may be potentially related to an increase in online purchases and stocking up groceries.

<sup>14</sup>Even though the number of cases is similar in late March and late May, public responses should have been stronger to the initial shock especially because they were not sure about the public health system at the beginning of the pandemic. In late May, when they become more convinced about the system, they likely adjusted their behavior accordingly. Existing evidence similarly shows recovery trends in credit card spending in the United States, where the number of COVID-19 cases continued to fluctuate (e.g., An et al., 2021; Chetty et al., 2020). Mobility trends in the United States are less comparable with our results because some US states used official stay-at-home order from time to time (Brough et al., 2021).

**TABLE 1** Descriptive statistics for regression variables

	Obs.	Mean	Median	S.D.
Cases in 14 days				
Total cases	46,592	0.533	0.000	1.578
Resident cases	46,592	0.226	0.000	0.674
Visitor cases	46,592	0.307	0.000	1.269
Outcome variables				
Nonresident inflows	46,592	49,512	43,918	27,579
Total spending (in million won)	44,584	1041	396	3865
Retail spending (in million won)	44,584	522	217	1696
% Change in 2019–2020				
Nonresident inflows	46,592	−10.601	−9.834	12.916
Total spending	44,584	−7.962	−10.888	29.372
Retail spending	44,584	−7.548	−12.002	40.055

*Note:* The unit of analysis is neighborhood-day, and the observations with the percent change in 2019–2020 greater than 95% or less than −95% were winsorized.

(e.g., Chetty et al., 2020) or the estimation of year-over-year (or month-over-month/day-over-day) changes in outcomes with some fixed effects (e.g., Janssen & Shapiro, 2020). For our analysis, we choose the latter approach to estimate the causal effects because we assume that case location disclosure arrives as exogenous shocks after we control for date- and neighborhood-specific trends of mobility and retail spending. Specifically, we employ the first-difference type of empirical models by calculating the year-over-year difference for our outcome variables. To identify the public behavioral responses to the case disclosure, we consider the following specification<sup>15</sup>:

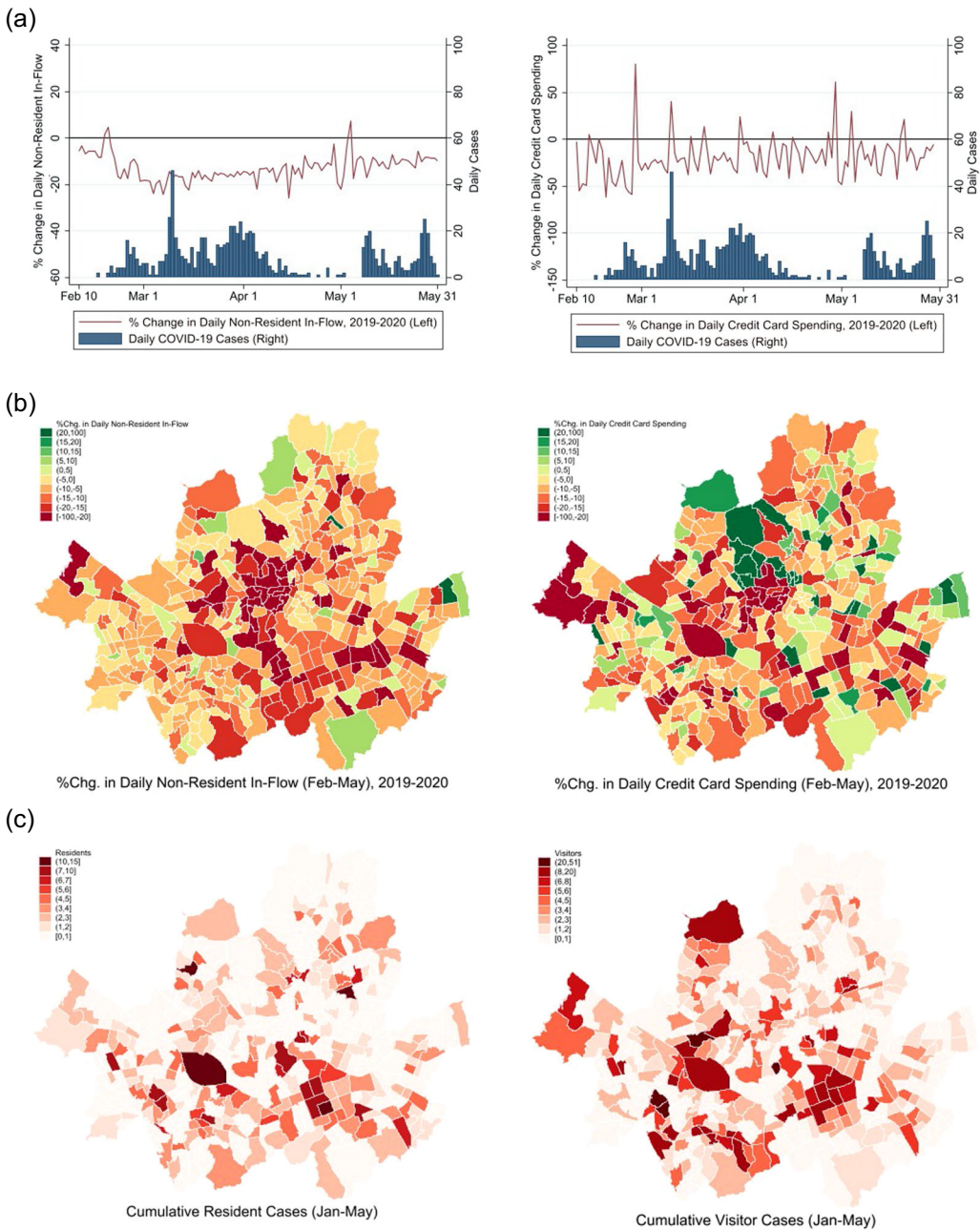
$$y_{i,t} = \beta_0 + \beta_s LocalCases_{i,s,t} + \sigma_i + \tau_t + \varepsilon_{i,t},$$

$$LocalCases_{i,s,t} = \sum_{k=1}^{14} COVID19_{i,s,t-k},$$

where  $y_{i,t}$  represents an outcome variable of interest: (1) the year-over-year percent change in nonresident flows and (2) the year-over-year percent change in (retail) credit card spending in *neighborhood i* on day  $t$ .  $COVID19_{i,s,t}$  denotes the number of disclosed COVID-19 cases for *neighborhood i* on day  $t$ , and  $s$  refers to three types of local cases: cases who reside in neighborhood  $i$  (resident), cases who visited neighborhood  $i$  (visitor), and the sum of both

<sup>15</sup>There are two reasons why we use resident and visitor cases separately along with the sum of these two. First, although concrete theory and evidence are still lacking with regard to the best methodology to estimate the impact of the disclosed location of COVID-19 cases, two studies that used the location information of COVID-19 cases used similar methodology. In their model to estimate the individual's probability of visiting a subregion  $j$  in Singapore, Janssen and Sapiro (2020) used as main explanatory variables both the number of case announcements for  $j$  and the number of positive cases who visited  $j$ . Xie and Milcheva (2020) used the distance between the location of property holdings of real estate firms and locations COVID-19 patients resided or visited as a main explanatory variable for the returns of these firms in Hong Kong. Second, the public has access to two different pieces of information on the disclosed location of COVID-19 cases: resident cases and visitor cases. As mentioned in the Background section, the process of information acquisition of these two is different. For the former, district offices in Seoul send text messages for every positive COVID-19 case to all cell phone users located within the same district as the case's residence. For the latter, the text is sent to request the public to report and get a test if they visited the same place as a confirmed COVID case visited in a given district or sometimes in Seoul. Public media are another source for information on the places visited by many confirmed COVID-19 cases. Because of this difference in information acquisition processes and search costs, we posit that the public would respond differently and explore three different specifications. For example, one potential hypothesis is that the information on hot spots of COVID-19 case visitors could be acquired more broadly by the public so they may have a more significant impact on the reduction in nonresident inflow and retail spending in a given neighborhood.





**FIGURE 1** Disclosed COVID-19 cases and changes in mobility and consumption in Seoul. (Panel A) Daily disclosed COVID-19 cases along with year-over-year percent changes in nonresident inflow (left) and credit card spending (right). (Panel B) Spatial heterogeneity in year-over-year percent changes in nonresident inflow (left) and credit card spending (right). (Panel C) Spatial distribution of COVID-19 cases through May 31, 2020: Resident (left) and visitor cases (right). Note: Spatial heterogeneity shown at the neighborhood level. A neighborhood, called “dong,” is the smallest administrative area, and there are 424 neighborhoods in Seoul [Color figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

numbers (total). Given that 14 days is known as the longest likely incubation period for COVID-19 and thus has been recommended as a quarantine period, we are interested in the effects of the number of publicly disclosed COVID-19 cases within the last 14 days,  $LocalCases_{i,s,t}$ . Individual neighborhood fixed effects  $\sigma_i$  absorb time-invariant area-specific factors, and date fixed effects  $\tau_t$  capture time-varying shocks that are common to all neighborhoods each day.

To examine more precisely the high frequency changes in an outcome variable before and after 2 weeks of COVID-19 case disclosure, we also run a dynamic model which is an event-study type of regressions with temporal trends. We use 14-day leads and lags of the number of neighborhood-level COVID-19 cases because its effects on nonresident inflow and retail spending change dynamically over time and would be rather transient, especially with the survival period of the virus and government disinfection measures.<sup>16</sup>

$$y_{i,t} = \beta_0 + \sum_{k=-14}^{14} \beta_{s,k} COVID19_{i,s,t-k} + \sigma_i + \tau_t + \varepsilon_{i,t},$$

where we specify the number of disclosed local COVID-19 cases for *neighborhood i* from 14 days ago to 14 days later (i.e., -14, -13, ..., +13, +14 days) from day *t*. In addition to these continuous variables, we also consider the dummy variables for COVID-19 cases (i.e., whether there was any disclosed case) from 14 days ago to 14 days later.

To test spatial heterogeneity in public responses to COVID-19 case disclosure, we add the interaction terms between local cases and neighborhood characteristics as follows:

$$y_{i,t} = \beta_0 + \lambda_s (LocalCases_{i,s,t} \times N_i) + \sigma_i + \tau_t + \varepsilon_{i,t},$$

where  $N_i$  is a set of neighborhood status dummies for spatial heterogeneity: top 20%, middle 60% (reference group), and bottom 20%. As mentioned above, we test whether the effects differ across neighborhoods with varying population density, employment density, land-use diversity, and retail agglomeration. While the estimated coefficients for the neighborhood status dummies will be absorbed in neighborhood fixed-effects, those for the interactions can be interpreted as the difference in the effects of public disclosure of COVID-19 cases between the neighborhood groups.

Finally, to test the potential spatial spillover or substitution from adjacent neighborhoods,<sup>17</sup> we add the number of cases tested positive in these neighborhoods controlling for the number of local cases as follows:

$$y_{i,t} = \beta_0 + \beta_s LocalCases_{i,s,t} + \gamma_{i,s,t} NeighborCases_{i,s,t} + \sigma_i + \tau_t + \varepsilon_{i,t},$$

where  $NeighborCases_{i,s,t}$  denotes (1) the number of case announcements for geographically or (2) functionally adjacent neighborhoods of *i* (neighbors), and *s* refers three different types of neighboring cases within the last 14 days as before. The geographically adjacent neighborhoods were identified as the neighborhoods that share a boundary and/or share a node using GIS techniques. The functionally adjacent neighborhoods are those within the same quintile of retail sales, which are not necessarily geographically adjacent.

<sup>16</sup>A longer-term pretrend analysis may be appropriate for more permanent changes, such as labor market outcomes. We acknowledge that even research using the DID design in the context of COVID-19 tends not to highlight the long-term pretrend probably because of the similar reason (e.g., Chetty et al., 2020).

<sup>17</sup>Spatial spillover effects are quite common in the spatial econometric literature. *Spatial substitution* is the term suggesting substitutability of a given spatial unit relative to alternative spatial units. It has been used frequently in the research on consumer spatial choice behavior, in particular, destination choice modeling (see Hunt et al., 2004; Lo, 1990, 1992).

## 5 | RESULTS

### 5.1 | Baseline regression results

Table 2 summarizes the regression results from the baseline models with public responses to disclosed COVID-19 cases with different outcomes: nonresident inflow (Panel A), total credit card spending (Panel B), and card spending in the retail sector, which is comprised of the “retail trade,” “tourism, entertainment, and recreation,” and “food services” industries (Panel C). We use four different combinations of the number of cases in a given neighborhood within the last 14 days: total cases (Model 1), resident cases (Model 2), visitor cases (Model 3), and resident and visitor cases separately (Model 4).

In all specifications, the number of disclosed COVID-19 cases reduced both mobility and consumer spending. For example, one additional COVID-19 case in a neighborhood over the last 14 days decreased nonresident inflow to the neighborhood by 0.40 percentage points compared with the same day the previous year (Panel A). Because we control for neighborhood- and date-fixed effects, this reduction is in addition to the neighborhood-specific general decline in foot traffic in 2020 compared with 2019 and the citywide reduction on the date. The result is consistent with Janssen and Shapiro (2020), who find a significant reduction in the probability of individuals to visit the subregion with more cases disclosed 1 day before. While the magnitudes of effects of disclosed information are not directly comparable because two studies use different empirical methods, it is interesting to find that resident cases have much stronger effects than visitor cases in their study compared with ours.<sup>18</sup>

Panel B indicates that the number of total COVID-19 cases in a neighborhood over the last 14 days decreased credit card spending in the neighborhood by 0.47 percentage points ( $p < 0.001$ ). When we compare results using a one standard deviation, the degree of reduction caused by the disclosed number of COVID-19 cases is larger for mobility than consumer spending.<sup>19</sup> While the effects of publicly disclosed information are similar between resident (0.49 percentage points with  $p$  value of 0.013, Model 2) and visitor cases (0.56 percentage points with  $p < 0.001$ , Model 3) when they are considered separately, the visitor case effects are greater when both are included in Model 4. A potential explanation is related to information search and acquisition. Public media tends to focus on the places visited by many confirmed COVID-19 cases, while text messages that include the case's residence information are sent to fewer local residents. Assuming that both involve lower search costs, therefore, most people would have acquired more information on visitor cases for destinations outside their own districts. This may also explain the different results between our study and Janssen and Shapiro (2020) mentioned above because information search costs are similar for resident and visitor cases in Singapore.

The results in Panel C of Table 2 present that, not surprisingly, the reduction is even greater for credit card spending in the retail sector, which includes industries that may be more vulnerable to COVID-19 shocks (e.g., restaurants, retail shops, and tourism). For example, while an additional COVID-19 case leads to the decline in overall credit card spending by 0.47 percentage points ( $p < 0.001$ ), the decline is concentrated in the retail sector where spending declined by 0.65 percentage points ( $p < 0.001$ ) per each COVID-19 case. This indicates that as a response to disclosed information of COVID-19 cases, people would reduce their mobility or avoid destinations with higher COVID-19 risks and pay even more attention to these risks when they want to dine out, go shopping, or watch a movie. When we repeat the regression analysis separately for “retail trade,” “tourism, entertainment, and

<sup>18</sup>Results suggest that the sum of coefficients for residents and visitors in separate regressions (Models 2 and 3) is larger than coefficients for Model 4. We believe this is related with nonlinearity rather than multicollinearity. First of all, we did not count the resident cases' visits for the visitor cases in a subject neighborhood so there should be no double counting. Also, spatial distribution of COVID-19 cases of residents and visitors seems to be quite random (see Figure 1, Panel C). To further address a potential concern on multicollinearity between resident and visitor cases, we performed the multicollinearity test, and the Variation Inflation Factor (VIF) values for those variables fall well below the rule of thumb threshold of 10, ranging from 1.31 to 1.34.

<sup>19</sup>Results suggest that a one standard deviation increase in the COVID-19 cases in the last 14 days (1.578) leads to a 0.048 standard deviation decrease in the nonresident inflows [ $-0.396 \times 1.578/12.916 = -0.048$ ]. For the credit card spending, using a one standard deviation of the COVID-19 cases in the last 14 days (1.578), the magnitude of the impact is a 0.025 standard deviation decrease [ $-0.466 \times 1.578/29.372 = -0.025$ ].

**TABLE 2** Baseline effects of disclosed COVID-19 cases on nonresident inflow and credit card spending

	Model 1	Model 2	Model 3	Model 4
<i>Panel A: Dependent variable: year-over-year percent change in nonresident inflow</i>				
Total cases in 14 days	-0.396*** (0.040)			
Residents in 14 days		-0.451*** (0.073)		-0.276*** (0.075)
Visitors in 14 days			-0.469*** (0.054)	-0.438*** (0.055)
Neighborhood FEs	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes
Number of Obs.	46,592	46,592	46,592	46,592
<i>Panel B: Dependent variable: year-over-year percent change in credit card spending</i>				
Total cases in 14 days	-0.466*** (0.076)			
Residents in 14 days		-0.490* (0.196)		-0.276 (0.200)
Visitors in 14 days			-0.561*** (0.089)	-0.531*** (0.090)
Neighborhood FEs	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes
Number of Obs.	44,584	44,584	44,584	44,584
<i>Panel C: Dependent variable: year-over-year percent change in retail credit card spending</i>				
Total cases in 14 days	-0.652*** (0.094)			
Residents in 14 days		-0.586* (0.291)		-0.271 (0.298)
Visitors in 14 days			-0.812*** (0.103)	-0.782*** (0.105)
Neighborhood FEs	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes
Number of Obs.	44,584	44,584	44,584	44,584

Note 1: \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ , and \*\*\*\* $p < 0.001$ . Robust standard errors in parentheses.

Note 2: The unit of analysis is neighborhood-day. The outliers with the percent change greater than 95% or less than -95% are excluded.

Note 3: Resident cases are the number of COVID-19 cases that reside in a given neighborhood. Visit cases are the number of nonresident COVID-19 patients that visited the neighborhood.

Note 4: The retail credit card spending refers to credit card spending in the retail sector, including retail trade, tourism, entertainment, recreation, and food services.

Abbreviation: FEs, fixed effects.

recreation," and "food services," the greatest effects are found in food services.<sup>20</sup> Given the findings, we will focus on the credit card spending in the retail sector for further analyses.

Next, considering a potential concern on the restrictive time horizon of the previous 14 days for counting COVID-19 cases in each neighborhood, we use an event-study type of specification with 14-day leads and lags. As shown in Table 3, the public responses to disclosed case information are quite immediate. With almost no pretrend before the date of disclosed information on the number of COVID-19 cases in a given neighborhood, we find a significant reduction in nonresident inflow to the neighborhood starting from 1 day after information disclosure. While the magnitude of the reduction becomes slightly smaller 5 days after information disclosure, it lasts for about 2 weeks. Results are consistent when we use the dummy variable for COVID-19 incidences in a given neighborhood instead of the number of cases (Panel A of Table 3 and Appendix A). Similarly, public responses with their retail spending reduction to disclosed location information of the number of COVID-19 cases start 1 day after information disclosure (Panel B of Table 3 and Appendix A). Although temporal patterns of this reduction are less linear compared with those for the reduction in nonresident inflow, these results demonstrate the robustness of our main results to the dynamic modeling approach.

Finally, we perform some robustness tests. Considering that the full sample analysis does not distinguish demand from commuters and noncommuters, we also try to stratify the sample by weekdays and weekends. As expected, the reductions in both mobility and retail spending are more significant for the subsample of weekends across most specifications, meaning that public responses were more active when they make discretionary choices (Appendix B).<sup>21</sup> We also run placebo regressions using the false numbers of COVID-19 cases that are randomly assigned to each neighborhood on a given date. As shown in Appendix C, results reveal no significant effect of COVID-19 cases on nonresident inflow and retail credit card spending.

## 5.2 | Spatial heterogeneity

We perform additional analysis to understand spatial heterogeneity in the effects of disclosed COVID-19 cases on nonresident inflow and retail credit card spending. We select top and bottom 20% neighborhoods in Seoul, by their population density, employment density, land-use mix, and retail agglomeration, and analyze heterogeneous results by neighborhood status in terms of these four categories (Tables 4 and 5).

Unlike existing evidence on the role of population density to the virus's spread (e.g., Wheaton & Kinsella Thompson, 2020), our results indicate that public responses to disclosed COVID-19 cases vary by different types of density. One additional COVID-19 case in a neighborhood in the bottom 20% for resident population density led to a decline of 0.68 percentage points ( $-0.680 = -0.422$  to  $0.258$ ,  $p < 0.001$ ) in nonresident inflow (Panel A, Table 4) and a decline of 1.20 percentage points ( $-1.196 = -0.621$  to  $0.575$ ,  $p < 0.001$ ) in retail spending (Panel A, Table 5). On the other hand, neighborhoods with higher population density experienced a much less severe decline in their local demand. For example, one additional COVID-19 case in the top 20% neighborhoods for resident population density increased nonresident inflow merely by 0.06 percentage points with  $p$  value of 0.700 (Panel A, Table 4). This is because people would prefer to make shorter trips in their own or nearby neighborhoods or perceive lower COVID-19 risk in largely residential areas. The heterogeneous results in retail spending by population density are in line with the existing evidence of growing consumption of groceries compared with a large reduction in spending for durable goods (An et al., 2021) as neighborhoods with higher population density are more likely to have grocery stores to serve local residents than large shops or department stores that sell durable goods and target a wider group of nonresident consumers.

<sup>20</sup>Results are not shown but available upon request.

<sup>21</sup>The number of visitor cases leads to a slightly higher reduction in retail spending for weekdays than weekends. Hence, commuters may be more sensitive to visitor case information than noncommuters when they choose location for retail activities.

Results on heterogeneity by employment density completely differ. Compared with the previous result by population density, neighborhoods across different levels of employment density show much less heterogeneous impacts of disclosed COVID-19 cases on mobility and consumption (Panel A, Tables 4 and 5). We believe that this is relevant to the institutional context of South Korea, which did not implement a

**TABLE 3** Event-study results for effects of disclosed COVID-19 cases on nonresident inflow and retail spending

	Panel A: Nonresident inflow			Panel B: Retail spending		
	Total	Residents	Visitors	Total	Residents	Visitors
Day -14	-0.311*	-0.407 <sup>+</sup>	-0.314*	0.020	-0.369	0.183
Day -13	-0.126	-0.290	-0.132	-0.850*	-0.771	-1.056*
Day -12	-0.170	-0.410 <sup>+</sup>	-0.095	-0.078	-0.476	0.181
Day -11	-0.099	-0.053	-0.185	0.378	1.079	-0.168
Day -10	-0.213	-0.288	-0.227	-0.089	-0.241	0.021
Day -9	-0.111	-0.428 <sup>+</sup>	-0.020	0.274	0.033	0.446
Day -8	0.033	-0.164	0.078	-0.075	0.267	-0.376
Day -7	-0.009	-0.019	-0.027	-0.689 <sup>+</sup>	-1.099	-0.480
Day -6	0.003	-0.008	-0.027	0.248	0.040	0.168
Day -5	-0.135	-0.359	-0.080	-0.555	-1.153	-0.377
Day -4	-0.077	-0.254	-0.057	0.178	-0.690	0.311
Day -3	-0.054	-0.069	-0.085	-0.080	-1.242	0.334
Day -2	-0.272*	-0.177	-0.389*	-0.720*	-0.699	-0.939*
Day -1	-0.246	-0.491*	-0.184	0.015	0.030	-0.133
Day 0	-0.205	-0.250	-0.324	-0.741 <sup>+</sup>	-1.139	-0.746
Day +1	-0.535**	-0.827***	-0.529*	-1.504***	-1.589 <sup>+</sup>	-1.678***
Day +2	-0.385*	-0.776**	-0.352 <sup>+</sup>	0.499	-0.083	0.638
Day +3	-0.430**	-0.474 <sup>+</sup>	-0.534*	-1.374***	-0.606	-1.971***
Day +4	-0.605***	-0.301	-0.846***	-0.974**	-1.425*	-1.030*
Day +5	-0.486**	-0.432	-0.573*	-0.980*	-1.865*	-0.722 <sup>+</sup>
Day +6	-0.386 <sup>+</sup>	-0.259	-0.513	-0.012	0.445	-0.412
Day +7	-0.404 <sup>+</sup>	-0.261	-0.584 <sup>+</sup>	-0.586	-0.267	-0.843
Day +8	-0.346 <sup>+</sup>	-0.674*	-0.295	-1.340*	-1.948*	-1.234*
Day +9	-0.318*	-0.593 <sup>+</sup>	-0.348 <sup>+</sup>	-0.392	-0.475	-0.579
Day +10	-0.218	-0.547*	-0.174	0.002	0.207	-0.092
Day +11	-0.516***	-0.467	-0.657**	-0.277	0.472	-0.609
Day +12	-0.451**	-0.538 <sup>+</sup>	-0.516**	-0.515	-0.281	-0.580
Day +13	-0.315	-0.505 <sup>+</sup>	-0.274	-0.826	-0.248	-1.225**
Day +14	-0.303	0.105	-0.537 <sup>+</sup>	-1.231*	-0.861	-1.473**

TABLE 3 (Continued)

	Panel A: Nonresident inflow			Panel B: Retail spending		
	Total	Residents	Visitors	Total	Residents	Visitors
Neighborhood FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	46,592	46,592	46,592	44,584	44,584	44,584

Note 1:  $^+p < 0.1$ ,  $^*p < 0.05$ ,  $^{**}p < 0.01$ , and  $^{***}p < 0.001$ . Robust standard errors in parentheses.

Note 2: The unit of analysis is neighborhood-day. The outliers with the percent change greater than 95% or less than -95% are excluded.

Note 3: Resident cases are the number of COVID-19 cases that reside in a given neighborhood. Visit cases are the number of nonresident COVID-19 patients that visited the neighborhood.

Note 4: The retail credit card spending refers to credit card spending in the retail sector including retail trade, tourism, entertainment, recreation, and food services.

Abbreviation: FEs, fixed effects.

substantial transition into remote working during our study period. Because of the mandatory nature of commuting trips, workers in Seoul would have continued to commute even when they perceive higher risk in neighborhoods concentrated with jobs and this may have led to a negligible difference in mobility and consumption between job centers and others. However, results in Table 5 (Panel A) suggest that retail spending declined by an additional 0.53 percentage point in the most job-concentrated neighborhoods when one additional visitor case was confirmed in these neighborhoods within the last 14 days. This indirectly suggests that even workers who were not able to avoid commuting may have reduced retail spending in their workplace neighborhoods when these neighborhoods experience a major outbreak with visits of many COVID-19 cases.<sup>22</sup>

Next, we test whether the effects of COVID-19 case disclosure vary by different levels of land-use diversity. It is measured by a Theil entropy score and has a greater value for the neighborhood with more mixed-use buildings and a lower value for the neighborhood largely dominated by single-use buildings. The results show that the disclosed COVID-19 cases, especially visitor cases, significantly reduced mobility into and retail spending in neighborhoods in the top 20% for land-use diversity, while the reduction was not statistically significant in those in the bottom 20% (Panel B, Tables 4 and 5). Given that the least diverse neighborhoods are largely dominated by residential properties (more than 70%) while the most diverse neighborhoods are mainly composed of commercial, transportation facilities, and/or mixed-use buildings, this echoes the above result on heterogeneity by resident population density.

Finally, we test the role of retail agglomeration to the effects of public disclosure of COVID-19 cases by selecting top/bottom 20% neighborhoods by their share of retail sales amount in 2015–2019.<sup>23</sup> Results suggest that an additional total COVID-19 case disclosed to the public reduced nonresident inflow to neighborhoods in the top 20% neighborhoods by 0.65 percentage points ( $p < 0.001$ ) while the same COVID-19 shock led to a 0.03 percentage point increase ( $p = 0.884$ ) in mobility into neighborhoods in the bottom 20% neighborhoods (Panel B,

<sup>22</sup>Also, these workers may have not received the text messages regarding resident cases in their workplace neighborhoods if they live in a different district (or even outside of Seoul), while major outbreaks, focusing on where many COVID-19 cases visited, were often covered by the media.

<sup>23</sup>While nonagglomerated areas should have had lower credit card spending in the prepandemic period, our dependent variable is not a year-over-year change in the net amount of spending but a year-over-year percent change. By doing this, we have accounted for the prepandemic levels. Another potential concern is that job losses and income reduction in more agglomerated neighborhoods could have spillovers on economic resilience on less agglomerated neighborhoods. However, as agglomerated neighborhoods would also have residents suffering from similar economic hardship in addition to a large effect from nonresident spending, they have likely experienced a lot more significant reduction in retail spending. In fact, we find that the magnitude of agglomeration effects is larger for retail spending than for nonresident inflow, which indicates that the dual effects of resident and nonresident spending exist.



**TABLE 4** Spatially heterogeneous effects of disclosed COVID-19 cases on nonresident inflow

<b>Panel A</b>						
<b>Spatial attribute</b>	<b>Population density</b>			<b>Employment density</b>		
<b>Case type</b>	<b>Total</b>	<b>Resident</b>	<b>Visitor</b>	<b>Total</b>	<b>Resident</b>	<b>Visitor</b>
_____ cases in 14 days	-0.422*** (0.057)	-0.612*** (0.089)	-0.462*** (0.066)	-0.361*** (0.059)	-0.347** (0.116)	-0.428*** (0.066)
(ref: Middle 60%)						
Top 20%	0.478** (0.155)	0.985*** (0.255)	0.360* (0.173)	-0.098 (0.139)	-0.228 (0.280)	-0.152 (0.163)
Bottom 20%	-0.258+ (0.153)	-0.111 (0.323)	-0.413* (0.187)	-0.185+ (0.101)	-0.290+ (0.161)	-0.212 (0.162)
Neighborhood FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	49,592	49,592	49,592	49,592	49,592	49,592
<b>Panel B</b>						
<b>Spatial attribute</b>	<b>Land-use diversity</b>			<b>Retail agglomeration</b>		
<b>Case type</b>	<b>Total</b>	<b>Resident</b>	<b>Visitor</b>	<b>Total</b>	<b>Resident</b>	<b>Visitor</b>
_____ cases in 14 days	-0.261*** (0.040)	-0.498*** (0.135)	-0.260*** (0.034)	-0.28*** (0.031)	-0.427*** (0.090)	-0.291*** (0.029)
(ref: Middle 60%)						
Top 20%	-0.657*** (0.108)	-0.057 (0.223)	-0.949*** (0.127)	-0.372*** (0.104)	-0.135 (0.220)	-0.563*** (0.118)
Bottom 20%	0.069 (0.061)	0.318* (0.149)	-0.024 (0.095)	0.311 (0.201)	0.128 (0.232)	1.012* (0.388)
Neighborhood FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	49,592	49,592	49,592	49,592	49,592	49,592

Note 1: + $p < 0.1$ , \* $p < 0.05$ , \*\* $p < 0.01$ , and \*\*\* $p < 0.001$ . Robust standard errors in parentheses.

Note 2: The unit of analysis is neighborhood-day. The outliers with the percent change greater than 95% or less than -95% are excluded.

Note 3: Resident cases are the number of COVID-19 cases that reside in a given neighborhood. Visit cases are the number of nonresident COVID-19 patients that visited the neighborhood.

Note 4: The retail credit card spending refers to credit card spending in the retail sector including retail trade, tourism, entertainment, recreation, and food services.

Note 5: Mixed land-use quintiles are assigned based on the Theil entropy score of building use (e.g., residential, commercial, industrial, and office) in a given neighborhood. Retail agglomeration quintiles are determined by the neighborhood's share of commercial building areas in Seoul in 2015–2019.

Abbreviation: FEs, fixed effects.

Table 4). With respect to retail spending, an increase in COVID-19 cases, especially visitor cases, leads to a significantly higher reduction in demand in the top 20% neighborhoods for retail agglomeration. These results suggest that neighborhoods that used to attract a lot of shoppers may be perceived as riskier and thus people may avoid visiting and spending money in the retail sector there.



**TABLE 5** Spatially heterogeneous effects of disclosed COVID-19 cases on retail credit card spending

Panel A						
Spatial attributes		Population density			Employment density	
Case type	Total	Resident	Visitor	Total	Resident	Visitor
_____cases in 14 days	-0.621*** (0.115)	-0.326 (0.369)	-0.800*** (0.122)	-0.603*** (0.100)	-0.716+ (0.397)	-0.685*** (0.102)
(ref: Middle 60%)						
Top 20%	0.190 (0.259)	-0.464 (0.628)	0.443 (0.271)	-0.116 (0.211)	0.640 (0.565)	-0.527* (0.258)
Bottom 20%	-0.575* (0.288)	-1.221* (0.606)	-0.590 (0.436)	-0.330 (0.394)	-0.329 (0.684)	-0.453 (0.655)
Neighborhood FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	44,584	44,584	44,584	44,584	44,584	44,584
Panel B						
Spatial attributes		Land-use diversity			Retail agglomeration	
Case type	Total	Resident	Visitor	Total	Resident	Visitor
_____cases in 14 days	-0.493*** (0.121)	-0.527 (0.451)	-0.583*** (0.125)	-0.565*** (0.098)	-0.996*** (0.232)	-0.564*** (0.110)
(ref: Middle 60%)						
Top 20%	-0.650*** (0.167)	0.120 (0.508)	-1.002*** (0.205)	-0.356* (0.160)	0.506 (0.334)	-0.719*** (0.194)
Bottom 20%	-0.194 (0.270)	-0.459 (0.679)	-0.184 (0.352)	0.820 (0.817)	1.696 (1.489)	0.366 (0.726)
Neighborhood FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	44,584	44,584	44,584	44,584	44,584	44,584

Note 1: \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ , and \*\*\*\* $p < 0.001$ . Robust standard errors in parentheses.

Note 2: The unit of analysis is neighborhood-day. The outliers with the percent change greater than 95% or less than -95% are excluded.

Note 3: Resident cases are the number of COVID-19 cases that reside in a given neighborhood. Visit cases are the number of nonresident COVID-19 patients that visited the neighborhood.

Note 4: The retail credit card spending refers to credit card spending in the retail sector including retail trade, tourism, entertainment, recreation, and food services.

Note 5: Mixed land-use quintiles are assigned based on the Theil entropy score of building use (e.g., residential, commercial, industrial, and office) in a given neighborhood. Retail agglomeration quintiles are determined by the neighborhood's share of commercial building areas in Seoul in 2015–2019.

Abbreviation: FEs, fixed effects.

**TABLE 6** Spatial spillover from geographically and functionally adjacent neighborhoods

Case type	Total		Resident		Visitor	
	Geographic	Functional	Geographic	Functional	Geographic	Functional
<i>Panel A: Dependent variable: year-over-year percent change in nonresident inflow</i>						
_____ cases of own	-0.335***	-0.372***	-0.347***	-0.448***	-0.42***	-0.442***
neighborhoods in 14 days	(0.048)	(0.049)	(0.084)	(0.085)	(0.059)	(0.059)
_____ cases in geographically adjacent	-0.057***		-0.212***		-0.062***	
neighborhoods in 14 days	(0.012)		(0.032)		(0.013)	
_____ cases in functionally adjacent		-0.026**		-0.069**		-0.029**
neighborhoods in 14 days		(0.009)		(0.025)		(0.010)
Neighborhood FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	49,592	49,592	49,592	49,592	49,592	49,592
<i>Panel B: Dependent variable: year-over-year percent change in retail credit card spending</i>						
_____ cases of own	-0.557***	-0.601***	-0.472 <sup>+</sup>	-0.585*	-0.714***	-0.740***
neighborhood in 14 days	(0.107)	(0.099)	(0.280)	(0.275)	(0.112)	(0.109)
_____ cases in geographically adjacent	-0.090*		-0.233*		-0.126*	
neighborhoods in 14 days	(0.045)		(0.094)		(0.051)	
_____ cases in functionally adjacent		-0.059***		-0.043		-0.082***
neighborhoods in 14 days		(0.014)		(0.030)		(0.017)
Neighborhood FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	44,584	44,584	44,584	44,584	44,584	44,584

Note 1: <sup>+</sup> $p < 0.1$ , \* $p < 0.05$ , \*\* $p < 0.01$ , and \*\*\* $p < 0.001$ . Robust standard errors in parentheses.

Note 2: The unit of analysis is neighborhood-day. The outliers with the percent change greater than 95% or less than -95% are excluded.

Note 3: Resident cases are the number of COVID-19 cases that reside in a given neighborhood. Visit cases are the number of nonresident COVID-19 patients that visited the neighborhood.

Note 4: The retail credit card spending refers to credit card spending in the retail sector, including retail trade, tourism, entertainment, recreation, and food services. Geographically adjacent neighborhoods are those that share a physical boundary and/or a node. Functionally adjacent neighborhoods are those in the same quintile for retail sales by ranking all neighborhoods in Seoul by retail credit card spending in 2015–2019.

Abbreviation: FEs, fixed effects.

### 5.3 | Spatial spillover versus substitution

Localized demand shock may be affected not only by disclosed information of COVID-19 cases in a given neighborhood but also by cases in adjacent neighborhoods.<sup>24</sup> To test this, we add the number of COVID-19 cases in the

<sup>24</sup>To identify geographically adjacent neighborhoods, we created a first-order contiguity spatial weights matrix (424 × 424) using ArcGIS 10.7.1.

geographically or functionally adjacent neighborhoods (i.e., those in the same quintile of retail sales within Seoul) to a given neighborhood.<sup>25</sup> The results are summarized in Table 6.

Controlling for the number of cases in a given neighborhood, one additional total case disclosed to the public in geographically adjacent neighborhoods led to a decrease of 0.06 percentage points ( $p < 0.001$ ) in nonresident inflow to the neighborhood (Panel A) and a decline of 0.09 percentage points ( $p = 0.048$ ) in retail spending (Panel B). The results also indicate that people were more sensitive to resident cases than visitor cases in geographically adjacent neighborhoods. One additional resident case in geographically adjacent neighborhoods led to a decrease of 0.21 percentage points ( $p < 0.001$ ) in nonresident inflow (Panel A) and a decline of 0.23 percentage points ( $p = 0.014$ ) in retail spending (Panel B). On the other hand, one additional visitor case in geographically adjacent neighborhoods led to a decrease of 0.06 ( $p < 0.001$ ) and 0.13 ( $p = 0.016$ ) percentage points in nonresident inflow (Panel A) and retail spending (Panel B), respectively. In other words, spatial spillover effects are greater when infected people reside in geographically adjacent neighborhoods rather than shortly visiting them. A big customer pool to a given neighborhood would be from residents in geographically adjacent neighborhoods because of shorter travel distances. As mentioned before, the cost for information acquisition is generally lower for resident cases for local residents because people get involuntary text messages from the district office. Hence, more resident cases in geographically adjacent neighborhoods are likely to reduce the travel demand of their residents to a given neighborhood.

We also examine the potential spillover or substitution effects of publicly disclosed COVID-19 cases in neighborhoods that are not necessarily geographically adjacent but are in the same quintile of retail sales. Since they are functionally similar, the subject neighborhood could be an alternative location for consumers if the neighborhood has fewer cases of COVID-19. The regression results in Panel A of Table 6 indicate that, however, there are negative spillover effects on nonresident inflows rather than substitution among neighborhoods that are functionally adjacent. Panel B also shows negative spillover effects on retail sales that are significant for both total and visitor cases. Therefore, whether it is geographic proximity or functional similarity, spatial spillover effects appear to dominate over substitution effects in the context of the COVID-19 pandemic.

## 6 | CONCLUSION

A policy to disclose the detailed location information of COVID-19 cases can be an effective measure to mitigate the virus's spread by promoting precautionary behavioral responses of the public. However, such information disclosure can also lead to substantial demand shocks, especially for retail businesses. If the distribution of COVID-19 cases has a significant spatial variation within a city, the demand shock would be localized at the neighborhood level. Moreover, if perceived risks of the virus's spread and behavioral responses differ by neighborhood attributes, such as the density of population or employment, land-use diversity, or retail agglomeration, the negative demand shock would be greater for certain neighborhoods than others even though they are reported to contain a similar number of COVID-19 cases.

We focus on these spatial implications in our study. Using the big data of daily mobility and credit card spending at the fine geographic level in Seoul, South Korea, we investigate public responses to the disclosed number of COVID-19 cases. We find that the public actively responded to the information disclosure by reducing their visits to and retail spending in neighborhoods with more cases. Moreover, there is spatial heterogeneity in public responses to the disclosed information of cases. People reduced visits and retail spending disproportionately more if neighborhoods have higher employment density, land-use diversity, and retail agglomeration. In contrast, neighborhoods with higher population density experienced little reduction in nonresident visits and retail spending. Finally, we demonstrate significant spatial spillover with no evidence on spatial substitution of localized demand toward neighborhoods with lower COVID-19 risks. The public further reduced their visits and retail spending if a

<sup>25</sup>The number of cases in its own neighborhood is excluded when calculating this number.

neighborhood is surrounded by areas with a higher number of COVID-19 cases or if COVID-19 risks increase in other areas with similar functions within the city.

Our findings suggest important implications for economic resilience of local neighborhoods during the pandemic period. Higher employment density and more mixed-use buildings in a neighborhood are associated with lower resilience. Retail agglomeration also appears to exacerbate local demand shock controlling for the number of COVID-19 cases. This is opposite from the evidence that areas with higher retail agglomeration were more resilient to economic crisis. In other words, spatial attributes that used to help the local economy may increase perceived COVID-19 risks and lead to lower economic resilience. On the other hand, stronger local demand and being located in more homogeneous residential areas help neighborhoods survive in terms of retail demand, potentially due to public preference for shorter trips as well as lower perceived risks of COVID-19. Also, in the context of COVID-19, demand substitution hardly occurs. Therefore, neighborhoods that used to be commercially viable would be the ones hit most severely during COVID-19.

These findings also call for more attention to localized economic impacts of the public health crisis and preparedness to future shocks. Our findings highlight that public responses to the COVID-19 pandemic significantly differ from those of natural disasters and economic crisis. Hence, cities' strategies to recover from the pandemic and strengthen the resilience of local communities have to reflect public concerns on social contacts and virus spread. For example, to revitalize commercial centers with agglomerated retail shops and high employment density, stronger safety measures should be considered. With respect to the policy measure of targeted social distancing through public information disclosure of COVID-19 cases, we not only echo existing evidence on its effectiveness and potentially lower economic cost compared with a lockdown (Argente et al., 2020) but also emphasize paying attention to the localized impact of this measure. Finally, we acknowledge both an advantage and disadvantage of using a sample from one large city. While it is more homogeneous in terms of spatial attributes and policy measures, there is a limitation of generalizability. Even with this limitation, we believe that our study is meaningful because Seoul is one of the most distinguished global cities. Global cities tend to show similar patterns of land uses and hierarchies of commercial spaces. Because Seoul is the rare case that has not gone through any lockdown during the pandemic, our results could provide important implications on urban resilience to other similar global cities.

## ACKNOWLEDGMENTS

We thank SK Telecom for providing the data. Financial support from the National University of Singapore (R-297-000-146-115) and Singapore Ministry of Education AcRF Tier 1 fund is gratefully acknowledged.

## DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from SK Telecom. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the author(s) with the permission of SK Telecom. I confirm that my Data Availability Statement complies with the Expects Data Policy. The data that support the findings of this study are available from SK Telecom and Hyundai Card. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors with the permission of SK Telecom and Hyundai Card.

## ORCID

Kwan Ok Lee  <https://orcid.org/0000-0003-2545-2591>

Hyojung Lee  <https://orcid.org/0000-0002-0471-6650>

## REFERENCES

- Abouk, R., & Heydari, B. (2021). The immediate effect of COVID-19 policies on social distancing behavior in the United States. *Public Health Reports*, 136(2), 245–252.

- Allcott, H., Boxell, L., Conway, J., Gentzkow, M., Thaler, M., & Yang, D. Y. (2020). *Polarization and public health: Partisan differences in social distancing during the Coronavirus pandemic* (NBER Working Paper, w26946).
- An, X., Cordell, L., Geng, L., & Lee, K. (2021). *Inequality in the time of COVID-19: Evidence from mortgage delinquency and forbearance* (Working Paper 3789349).
- Andersen, M. (2020). *Early evidence on social distancing in response to COVID-19 in the United States* (Working Paper 3659368).
- Argente, D. O., Hsieh, C. T., & Lee, M. (2020). *The cost of privacy: Welfare effect of the disclosure of COVID-19 cases* (Vol. w27220). National Bureau of Economic Research.
- Baker, S. R., Farrokhnia, R. A., Meyer, S., Pagel, M., & Yannelis, C. (2020). *How does household spending respond to an epidemic? Consumption during the 2020 COVID-19 pandemic* (Vol. w26949). National Bureau of Economic Research.
- Béland, L.-P., Brodeur, A., & Wright, T. (2020). *The short-term economic consequences of COVID-19: Exposure to disease, remote work and government response* (IZA DP No. 13159).
- Bernstein, J., Richter, A. W., & Throckmorton, N. A. (2020). *COVID-19: A view from the labor market* (Working Paper).
- Brough, R., Freedman, M., & Phillips, D. C. (2021). Understanding socioeconomic disparities in travel behavior during the COVID-19 pandemic. *Journal of Regional Science*, 61(4), 753–774. <http://doi.org/10.1111/jors.12527>
- Brown, S. (1989). Retail location theory: The legacy of Harold Hotelling. *Journal of Retailing*, 65(4), 450–470.
- Capello, R., Caragliu, A., & Fratesi, U. (2015). Spatial heterogeneity in the costs of the economic crisis in Europe: Are cities sources of regional resilience? *Journal of Economic Geography*, 15(5), 951–972.
- Carvalho, V. M., Garcia, J. R., Hansen, S., Ortiz, A., Rodrigo, T., Mora, J. V. R. & Ruiz, J. (2020). Tracking the COVID-19 crisis with high-resolution transaction data (Cambridge Working Papers in Economics CWPE2030).
- Chen, H., Qian, W., & Wen, Q. (2021). The Impact of the COVID-19 Pandemic on Consumption: Learning from High-Frequency Transaction Data. *AEA Papers and Proceedings*, 111, 307–311. <http://doi.org/10.1257/pandp.20211003>
- Chen, Y., Jiao, J., Bai, S., & Lindquist, J. (2020). *Modeling the spatial factors of COVID-19 in New York City* (Working Paper 3606719).
- Chetty, R., Friedman, J. N., Hendren, N., & Stepner, M., & The Opportunity Insights Team. (2020). *How did COVID-19 and stabilization policies affect spending and employment? A new real-time economic tracker based on private sector data* (pp. 1–109). National Bureau of Economic Research.
- Coibion, O., Gorodnichenko, Y., & Weber, M. (2020). *The cost of the COVID-19 Crisis: Lockdowns, macroeconomic expectations, and consumer spending* (NBER Working Paper w27141).
- Courtemanche, C. J., Garuccio, J., Le, A., Pinkston, J. C., & Yelowitz, A. (2020). *Did social-distancing measures in Kentucky help to flatten the COVID-19 curve?* (Working Paper).
- Dave, D. M., Friedson, A. I., Matsuzawa, K., Sabia, J. J., & Safford, S. (2020). *Were urban cowboys enough to control COVID-19? Local shelter-in-place orders and coronavirus case growth* (Vol. w27229). National Bureau of Economic Research.
- Farboodi, M., Jarosch, G., & Shimer, R. (2020). *Internal and external effects of social distancing in a pandemic* (Vol. w27059). National Bureau of Economic Research.
- Fetzer, T., Hensel, L., Hermle, J., & Roth, C. (2021). Coronavirus perceptions and economic anxiety. *The Review of Economics and Statistics*, 1–11. [http://doi.org/10.1162/rest\\_a\\_00946](http://doi.org/10.1162/rest_a_00946)
- Gupta, S., Nguyen, T. D., Rojas, F. L., Raman, S., Lee, B., Bento, A., Simon, K. I., & Wing, C. (2020). *Tracking public and private response to the covid-19 epidemic: Evidence from state and local government actions* (Vol. w27027). National Bureau of Economic Research.
- Hamermesh, D. S. (2020). *Lock-downs, loneliness and life satisfaction* (Vol. w27018). National Bureau of Economic Research.
- Hunt, L. M., Boots, B., & Kanaroglou, P. S. (2004). Spatial choice modelling: New opportunities to incorporate space into substitution patterns. *Progress in Human Geography*, 28(6), 746–766.
- Janssen, A., & Shapiro, M. H. (2020). *Does precise case information limit precautionary behavior? Evidence from COVID-19 in Singapore* (Working Paper).
- Kahn, L. B., Lange, F., & Wiczer, D. G. (2020). *Labor Demand in the time of COVID-19: Evidence from vacancy postings and UI claims* (p. w27061). NBER
- Kosfeld, R., Mitze, T., Rode, J., & Wälde, K. (2021). The Covid-19 containment effects of public health measures: A spatial difference-in-differences approach. *Journal of Regional Science*, 61, 799–825.
- Lo, L. (1990). A translog approach to consumer spatial behavior. *Journal of Regional Science*, 30(3), 393–413.
- Lo, L. (1992). Destination interdependence and the competing-destinations model. *Environment and Planning A*, 24(8), 1191–1204.
- Lu, R., Wu, X., Wan, Z., Li, Y., Zuo, L., Qin, J., Jin, X., & Zhang, C. (2020). Development of a novel reverse transcription loop-mediated isothermal amplification method for rapid detection of SARS-CoV-2. *Virologica Sinica*, 35, 1–347.
- Malaloda, C., Amaratunga, D., & Haigh, R. (2013). Creating a disaster resilient built environment in urban cities. *International Journal of Disaster Resilience in the Built Environment*, 4, 72–94.

- Marcén, M., & Morales, M. (2021). The intensity of COVID-19 non-pharmaceutical interventions and labor market outcomes in the public sector. *Journal of Regional Science*, 61, 775–798.
- Massey, D. S., & Denton, N. A. (1988). The dimensions of residential segregation. *Social Forces*, 67(2), 281–315.
- Meltzer, R., Ellen, I. G., & Li, X. (2020). Localized commercial effects from natural disasters: The case of Hurricane Sandy and New York City. *Regional Science and Urban Economics*, 86, 103608.
- Nelson, R. L. (1958). *The selection of retail locations*. FW Dodge Corporation.
- Nguyen, T. D., Gupta, S., Andersen, M., Bento, A., Simon, K. I., & Wing, C. (2020). *Impacts of state reopening policy on human mobility* (Vol. w27235). National Bureau of Economic Research.
- Painter, M., & Qiu, T. (2020). *Political beliefs affect compliance with covid-19 social distancing orders* (Working Paper 3569098).
- Reimers, V., & Clulow, V. (2004). Retail concentration: A comparison of spatial convenience in shopping strips and shopping centres. *Journal of Retailing and Consumer Services*, 11(4), 207–221.
- Rojas, F. L., Jiang, X., Montenegro, L., Simon, K. I., Weinberg, B. A., & Wing, C. (2020). *Is the cure worse than the problem itself? Immediate labor market effects of COVID-19 case rates and school closures in the US* (Vol. w27127). National Bureau of Economic Research.
- Siedner, M. J., Harling, G., Reynolds, Z., Gilbert, R. F., Venkataramani, A., & Tsai, A. C. (2020). Social distancing to slow the US COVID-19 epidemic: An interrupted time-series analysis. *PLOS Medicine*, 17(10), e1003376.
- Stevens, M. R., Song, Y., & Berke, P. R. (2010). New urbanist developments in flood-prone areas: Safe development, or safe development paradox? *Natural Hazards*, 53(3), 605–629.
- Surico, P., Känzig, D., & Hacıoglu, S. (2020). *Consumption in the time of COVID-19: Evidence from UK transaction data* (CEPR Discussion Paper 14733).
- Tucker, C. E., & Yu, S. (2020). *The early effects of coronavirus-related social distancing restrictions on brands* (Working Paper 3566612).
- Wamsler, C., Brink, E., & Rivera, C. (2013). Planning for climate change in urban areas: From theory to practice. *Journal of Cleaner Production*, 50, 68–81.
- Wheaton, W. C., & Kinsella Thompson, A. (2020). *Doubts about density: COVID-19 across cities and towns* (Working Paper 3586081).
- Wrigley, N., & Dolega, L. (2011). Resilience, fragility, and adaptation: New evidence on the performance of UK high streets during global economic crisis and its policy implications. *Environment and Planning A*, 43(10), 2337–2363.
- Xie, L., & Micheva, S. (2020). *Proximity to COVID-19 Cases and Real Estate Equity Returns*. Working paper.

**How to cite this article:** Lee, K. O., & Lee, H. (2021). Public responses to COVID-19 case disclosure and their spatial implications. *Journal of Regional Science*, 1–25. <https://doi.org/10.1111/jors.12571>

## APPENDIX A: EVENT-STUDY RESULTS WITH ALTERNATIVE SPECIFICATIONS: DUMMY VARIABLES FOR COVID-19 CASES

	Panel A: Nonresident inflow			Panel B: Retail spending		
	Total	Residents	Visitors	Total	Residents	Visitors
Day -14	-0.470*	-0.547 <sup>+</sup>	-0.602*	-0.380	-1.454	0.418
Day -13	-0.359 <sup>+</sup>	-0.405	-0.385	-1.565*	-1.377	-1.144
Day -12	-0.433*	-0.542*	-0.391	-1.787**	-0.382	-2.438**
Day -11	-0.025	-0.041	-0.030	-0.277	0.996	-1.028
Day -10	-0.429 <sup>+</sup>	-0.157	-0.752*	-0.173	-0.367	0.001
Day -9	-0.230	-0.512	-0.094	0.364	-0.364	0.577
Day -8	-0.062	-0.137	-0.031	-0.570	-0.352	-0.619
Day -7	0.022	0.044	-0.072	-1.597*	-1.794 <sup>+</sup>	-1.273
Day -6	0.175	-0.027	0.253	0.502	0.472	0.325
Day -5	-0.407 <sup>+</sup>	-0.193	-0.728*	-0.430	-1.167	-0.138
Day -4	-0.265	-0.098	-0.503 <sup>+</sup>	-0.338	-0.798	0.244
Day -3	-0.129	-0.027	-0.257	-0.094	-1.250	0.865

	Panel A: Nonresident inflow			Panel B: Retail spending		
	Total	Residents	Visitors	Total	Residents	Visitors
Day -2	-0.097	-0.083	-0.280	-1.542*	-1.567	-1.445
Day -1	-0.462*	-0.578 <sup>+</sup>	-0.460 <sup>+</sup>	-0.006	-0.116	-0.081
Day 0	-0.305	-0.276	-0.451	-1.879**	-1.460	-1.877*
Day +1	-0.885***	-0.981**	-0.753*	-2.373**	-1.972 <sup>+</sup>	-2.842**
Day +2	-0.706**	-0.852*	-0.727*	0.480	-0.704	0.755
Day +3	-0.898***	-0.554	-1.298***	-2.372***	-0.565	-3.808***
Day +4	-0.933***	-0.476	-1.375***	-2.090***	-2.267**	-2.047**
Day +5	-0.728**	-0.604 <sup>+</sup>	-0.925**	-1.801*	-2.200 <sup>+</sup>	-1.477 <sup>+</sup>
Day +6	-0.784***	-0.607 <sup>+</sup>	-1.043***	-0.043	1.134	-1.349 <sup>+</sup>
Day +7	-0.656**	-0.516	-0.959**	-1.467*	-0.900	-1.800*
Day +8	-0.719**	-0.982**	-0.569 <sup>+</sup>	-2.864***	-2.254 <sup>+</sup>	-3.067***
Day +9	-0.618*	-0.956**	-0.569 <sup>+</sup>	-0.236	-0.063	-0.619
Day +10	-0.501*	-0.636 <sup>+</sup>	-0.603 <sup>+</sup>	-0.196	0.786	-1.121
Day +11	-0.889***	-0.734 <sup>+</sup>	-1.146***	-0.947	0.428	-2.088**
Day +12	-0.644**	-0.853**	-0.550 <sup>+</sup>	-1.538*	-1.040	-1.851*
Day +13	-0.616**	-0.786*	-0.497 <sup>+</sup>	-0.309	0.319	-1.391
Day +14	-0.494*	-0.23	-0.730*	-0.907	-0.700	-1.498
Neighborhood FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	46,592	46,592	46,592	44,584	44,584	44,584

Note 1: <sup>+</sup> $p < 0.1$ , \* $p < 0.05$ , \*\* $p < 0.01$ , and \*\*\* $p < 0.001$ . Robust standard errors in parentheses; FEs, fixed effects.

Note 2: The unit of analysis is neighborhood-day. The outliers with the percent change greater than 95% or less than -95% are excluded.

Note 3: Resident cases are the number of COVID-19 cases that reside in a given neighborhood. Visit cases are the number of nonresident COVID-19 patients that visited the neighborhood.

Note 4: The retail credit card spending refers to credit card spending in the retail sector, including retail trade, tourism, entertainment, recreation, and food services.

APPENDIX B: SUMMARIZED REGRESSION RESULTS OF EFFECTS ON NONRESIDENT INFLOW AND RETAIL CREDIT CARD SPENDING, WITH THE SAMPLE STRATIFIED BY WEEKDAYS VERSUS WEEKENDS

	Total		Resident		Visitor	
	All		All		All	
Panel A: Dependent variable: year-over-year percent change in nonresident inflow						
—cases in 14 days	–0.396*** (0.040)	–0.362*** (0.040)	–0.463*** (0.082)	–0.451*** (0.073)	–0.469*** (0.054)	–0.413*** (0.053)
Neighborhood FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	46,592	33,886	12,706	46,592	46,592	33,886
Panel B: Dependent variable: year-over-year percent change in retail credit card spending						
—cases in 14 days	–0.652*** (0.094)	–0.670*** (0.121)	–0.614*** (0.129)	–0.586* (0.291)	–0.812*** (0.103)	–0.882*** (0.128)
Neighborhood FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	44,584	32,288	12,296	44,584	44,584	32,288

Note 1: \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.001$ . Robust standard errors in parentheses; FEs, fixed effects.

Note 2: The unit of analysis is neighborhood-day. The outliers with the percent change greater than 95% or less than –95% are excluded.

Note 3: Resident cases are the number of COVID-19 cases that reside in a given neighborhood. Visit cases are the number of nonresident COVID-19 patients that visited the neighborhood.

Note 4: The retail credit card spending refers to credit card spending in the retail sector including retail trade, tourism, entertainment, recreation, and food services.



## APPENDIX C: PLACEBO TESTS BY APPLYING THE RANDOM NUMBERS OF COVID-19 CASES

	Model 1	Model 2	Model 3	Model 4
<i>Panel A: Dependent variable: year-over-year percent change in nonresident inflow</i>				
Total cases in 14 days	-0.044 (0.054)			
Residents in 14 days		-0.081 (0.088)		-0.080 (0.088)
Visitors in 14 days			-0.011 (0.070)	-0.010 (0.070)
Neighborhood FEs	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes
Number of Obs.	46,592	46,592	46,592	46,592
<i>Panel B: Dependent variable: year-over-year percent change in retail credit card spending</i>				
Total cases in 14 days	0.234 (0.254)			
Residents in 14 days		0.258 (0.357)		0.257 (0.357)
Visitors in 14 days			0.212 (0.384)	0.211 (0.384)
Neighborhood FEs	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes
Number of Obs.	44,584	44,584	44,584	44,584

Note 1:  $^{\dagger}p < 0.1$ ,  $^*p < 0.05$ ,  $^{**}p < 0.01$ , and  $^{***}p < 0.001$ . Robust standard errors in parentheses; FEs, fixed effects.

Note 2: The unit of analysis is neighborhood-day. The outliers with the percent change greater than 95% or less than -95% are excluded.

Note 3: Resident cases are the number of COVID-19 cases that reside in a given neighborhood. Visit cases are the number of nonresident COVID-19 patients that visited the neighborhood.

Note 4: The retail credit card spending refers to credit card spending in the retail sector including retail trade, tourism, entertainment, recreation, and food services.