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Economic impact of targeted government responses to COVID-19: Evidence from the large-scale clusters in Seoul

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A B S T R A C T
We estimate the economic impact of South Korea’s targeted responses to the large-scale COVID-19 clusters in a highly concentrated business area (Guro) and a highly concentrated entertainment area (Itaewon) in Seoul, respectively. We find that foot traffic and retail sales decreased only within a 300 m radius and recovered to their pre-outbreak level after four weeks in the case of the Guro cluster. The reductions appear to be driven by temporary business closures rather than by citizens’ risk avoidance behavior. However, the adverse economic impacts measured by foot traffic and retail sales of another outbreak of the COVID-19 cluster in Itaewon were persistent. Our results imply that the effects of less intense but more targeted COVID-19 interventions, such as pinpointed, temporary closures of businesses, can differ by underlying geographical characteristics.

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1. Introduction

Most governments worldwide have relied on massive non-pharmaceutical interventions (NPI) to contain the spread of the novel coronavirus disease (COVID-19), such as business and school closures, stay-at-home orders, bans on social gatherings, and restrictions on local and international travels (Hale et al., 2020). However, despite the clear health benefits, strict social distancing policies can lead to prolonged economic recession. Several studies estimate the high economic costs of intense NPIs, such as shelter-in-place orders, or economy-wide lockdowns (Alexander and Kager, 2021; Anderson et al., 2020; Baker et al., 2020; Carvalho et al., 2020; Chen et al., 2021; Coibion et al., 2020; Kim et al., 2021).

Recent simulation-based studies that investigate trade-offs between health benefits and economic costs by the type and intensity of NPIs, predict that the pandemic can be controlled without complete lockdowns (Acemoglu et al., 2020;...
Alternative types of lower-intensity NPIs, such as small-scale lockdowns of individual COVID-19 clusters can be an efficient approach for controlling disease spread without significant economic costs because they are likely to cause smaller disruptions to the economy. Many countries have been transitioning to mild social distancing measures to minimize the adverse economic costs of severe lockdowns. However, there is limited empirical evidence on the economic impact of less severe but more targeted NPIs.

We fill this gap in the literature by investigating the effects of South Korea’s targeted responses to the large-scale COVID-19 clusters in Seoul. The first outbreak of a local cluster originated from a large call center in Guro, one of the busiest urban areas in Seoul, infected 166 individuals and could potentially have contributed to an explosion of local transmission (Park et al., 2020). We argue that this cluster outbreak provides a unique context for studying the effect of less intense but more targeted NPIs. First, the Korean government’s response to this cluster was a standard strategy in the fight against COVID-19, which can be adopted by other governments considering lifting strict social distancing measures and in a future pandemic. The day after the first case in the cluster, the Korea Centers for Disease Control and Prevention (KCDC) and local governments organized a joint response team and enforced two-week closures of businesses operating in the building where the call center was located. Additionally, the joint response team implemented rapid and meticulous contact tracing, extensive testing, and encouraged voluntary risk avoidance behavior by the citizens via public disclosure of the detailed location information of the COVID-19 positive patients and timelines. The situation was completely contained after 25 days (i.e., no additional cases linked to the cluster).

For the empirical analysis, we use foot traffic and retail sales transaction data measured at a high-frequency granular level and apply a difference-in-differences (DID) method to compare the changes in foot traffic and retail sales within the immediate proximity of the cluster and its surrounding areas before and after the public announcement of the cluster. We note sharp declines in foot traffic and retail sales within the cluster’s 300 m (0.19 mile) radius during the first two weeks after the outbreak. However, there is no evidence that foot traffic and retail sales decreased beyond a 300-meter radius. The reductions in foot traffic and retail sales within the 300 m radius started to rebound after two weeks and recovered to their pre-outbreak level after a month. Older adults are at a significantly greater risk of developing severe illness if exposed to the novel coronavirus (Lian et al., 2020; Shahid et al., 2020). Thus, they may have had a stronger incentive to avoid the risk of infection and decrease foot traffic and spending. However, our heterogeneity analysis reveals that reductions in foot traffic and sales were higher among younger individuals. Given that individuals immediately linked to the call center cluster were, on average, 38 years old (Park et al., 2020), the baseline economic impact is likely to be driven by young workers whose workplace was temporarily closed after the outbreak in the cluster.

Since the Guro call center case was the first COVID-19 cluster in South Korea which generated much media attention, individuals’ responses to the following clusters could have differed. To assess the external validity of our baseline findings, we study foot traffic and sales responses to the outbreak of another large COVID-19 cluster in Itaewon, a neighborhood with high-density entertainment outlets (night clubs and lounges) in Seoul. Unlike foot traffic and sales responses to the Guro call center cluster, we document that the adverse economic impact of the Itaewon cluster was persistent for at least six weeks, especially during the weekend.

The findings suggest that the economic costs of the Korean government’s targeted responses to the first large-scale COVID-19 cluster in Seoul are heterogeneous. The cluster in a highly concentrated business area was local and temporary, while a cluster in a highly concentrated entertainment area was more persistent. One possible explanation for the heterogeneous economic impacts of these two types of COVID-19 clusters could be the role of risk-avoiding behavior by individuals. In a high-density entertainment area, individuals may expect a higher probability of infection via human interactions, thereby discouraging them from visiting the area after the cluster outbreak. We argue that this study can provide valuable insights into tackling the prolonged COVID-19 situation while protecting the economy. Several countries are lifting strict social distancing measures even as the virus is still raging to alleviate the adverse economic costs, even as novel variants of the virus continue to evolve. In the U.S., Bartik et al. (2020) document that small business owners’ expected length of COVID-19 leads to a lower likelihood of operating their businesses and argue for significant economic benefits of short-term NPIs such as localized temporary lockdowns. Our results indicate that a short-term containment policy should be implemented with extra care to minimize the actual economic costs, as measured by foot traffic and retail sales.

This study contributes to the literature by providing new evidence on the economic costs of targeted NPIs in a COVID-19 cluster. Previous studies quantifying the impact of a localized shock on the local economy document that the public disclosure of information about a sex criminal’s move-in temporarily reduces the sales prices of nearby homes in the U.S. and South Korea (Linden and Rockoff, 2008; Pope, 2008; Kim and Lee, 2018). As more countries have lifted massive lockdowns and are implementing more targeted and temporary NPIs, policymakers and researchers need to understand the effects of the targeted NPIs on the local economy. Although an increasing number of studies have investigated the spending response of consumers to COVID-19, they have examined the economic costs through counterfactual simulations using augmented SIR

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1 Fig. 1 shows that the call center is located near two subway stations (Guro and Sindorim) and surrounded by high-rise apartment buildings. A large department store and Walmart-like hypermarket chains are also located within a 500–900 m (.31–.56 mile) radius from the cluster.

2 Appendix B provides details of the Korean government’s responses to COVID-19.
epidemiology models (Acemoglu et al., 2020; Argente et al., 2020; Fajgelbaum et al., 2021). We complement the literature by providing reduced-form evidence of the spatial distribution and persistence of the economic cost of micro-targeted NPIs. The remainder of this study proceeds as follows. Section 2 details the background to the COVID-19 situation in South Korea, and the COVID–19 cluster that originated from a large call center in Seoul. Sections 3 and 4 describe the data and empirical strategy, respectively. Section 5 discusses the results. Section 6 presents the conclusions.

2. COVID–19 situation in South Korea and the Guro call center cluster

The first case of COVID–19 in South Korea was reported on January 20, 2020. During the early stages of the outbreak, the number of confirmed cases increased sharply, with the majority of new infections in the southeastern region of South Korea (Daegu and Gyeongangbuk-do) owing to mass gatherings of the Shincheonji Church of Jesus with more than 310,000 members (KCDC, 2020). South Korea has a population of approximately 52 million, and as of October 9, 2021, it has recorded 2560 deaths attributed to COVID–19.

The first case from the Guro call center cluster was confirmed on March 8, 2020. Fig. A1 shows a sharp increase in the number of confirmed cases linked to this cluster for the first two days following the first case. The KCDC and local governments formed a joint response team and launched epidemiological investigations immediately after discovering multiple cases. On March 9, 2020, after confirming more than 20 cases, the 19-story building housing the call center was ordered to close for two weeks. On March 10, the Mayor of Seoul declared the Guro call center case as the first large-scale cluster in the city. As this was the first large-scale cluster, the media covered the details of the situation in depth. Consequently, the general public learned about the call center cluster almost immediately. Following the public announcement of the cluster, the number of news articles and keyword searches about the call center case recorded an immediate increase on Google and the most popular web search engine (NAVER) in South Korea, as shown in Fig. A2.

The government tested 99.8% of individuals working or living in the building or who had visited it two weeks before March 8 (Park et al., 2020). Confirmed positive patients were isolated, whereas those testing negative were mandated to stay self-quarantined at home for 14 days. The joint response team investigated, tested, and monitored household contacts of all confirmed positive patients for 14 days after discovering the cluster, regardless of symptoms. During March 13–16, 2020, the government used people’s mobile phone signal data and sent 16,628 text messages to people who were found to have spent more than 5 min in the vicinity of the building. The messages instructed recipients to avoid contact with people and visit the nearest COVID–19 screening station for testing. The Guro call center cluster was contained completely after 25 days, as there were no more positive patients linked to this cluster.

3. Data

We use two data sources: census block-level information on foot traffic and retail sales in Seoul. First, we use hourly estimates of foot traffic (i.e., individuals physically present at the time) based on mobile phone signals. KT, the second-largest mobile telecom carrier in South Korea with a market share of 26%, provides these estimates based on their proprietary cell phone signal data using the following procedures: (1) KT calculates the amount of foot traffic by collecting mobile signals for each signal tower at a specific time; (2) it adjusts this number using its market share, mobile usage ratio, and the on/off ratio of mobile signals in each block. (3) KT further adjusts the block-specific foot traffic using census block characteristics because some census blocks have multiple signal towers.

Second, we use the estimates of daily retail sales based on data from card transactions. Shinhan Card, the largest credit card company in South Korea with a market share of 22%, provides these computed estimates based on proprietary card transaction data. Shinhan Card uses transaction records from the payment terminal of each store and estimates the total sales of each block using additional information such as the market share of the card company and the card usage patterns based on sector, region, time, and demographic subgroups.

For the empirical analysis, we construct the block and week-level panel data covering 123 blocks in the vicinity of the COVID–19 cluster and 11 weeks between February 3 and April 19, 2020. Table 1 shows the descriptive statistics of foot traffic and retail sales. Column (1) indicates that the average hourly foot traffic per block is approximately 500, implying that, on average, 500 individuals are present per block within a 900 m radius in each hour. The average hourly foot traffic within a 100 m radius of the cluster is about 760 individuals, higher than other blocks at longer distances from the cluster. This is because the call center building is located in a highly concentrated business area. The average hourly foot traffic level within a 100–500 m radius is about 330–360 individuals, which is less than the 500–900 m radius, having approximately 590 individuals, because hypermarkets and a large-scale department store are located within a 500–900 m-radius of the cluster.

3 To evaluate the economic cost of targeted NPIs compared to other interventions (e.g., large-scale NPIs, no intervention), counterfactual simulations of different interventions after estimating a full-fledged structural model would be most appropriate. This paper cannot provide such evidence.

4 A census block is the minimal geographical unit classified by the statistical office of South Korea. The size of a census block is less than 0.1 km² (approximately 0.04 square mile) on average. There are 19,153 blocks in Seoul.

5 For the details, visit http://data.seoul.go.kr/dataVisual/seoul/seoulLivingPopulation.do.

6 The results, available upon request, are similar but noisier when using block- and day-level panel data.

7 The average hourly foot traffic increases to 1219 if we restrict the sample to the data collected during working hours (i.e., between 9 am and 6 pm).
Column (2) reveals that the average daily sales amount per block is approximately 21 million Korean won (US$17,456).8 Contrary to the fact that the average foot traffic is the largest within a 100 m radius, the average sales amount within a 100 m radius is the smallest. Most retail sales take place in blocks at a distance of 500–900 m from the cluster owing to the presence of hypermarkets and a large department store.

4. Empirical strategy

To identify the spatial distribution of the economic cost of the first COVID-19 cluster in Seoul and its persistence, we compare changes in foot traffic and retail sales in the immediate and surrounding areas before and after the public announcement of the cluster. Fig. A3 shows the trends of the logarithm values for foot traffic and retail sales during weekdays in panels A and B, respectively. The trends indicate that, following the announcement of the cluster, the foot traffic and retail sales reduced sharply within a 300 m radius. The declines within a 100-meter radius were greater than the 100–300 m radius. However, it began to rebound two weeks after the cluster outbreak. Furthermore, little changes were observed in foot traffic and sales within the cluster’s 300–900 m radius. We employ the following difference-in-differences (DID) regression model to estimate the changes in foot traffic and retail sales:

\[ y_{i,d,t} = \beta_0 + \sum_{d=5} \sum_{t=0} \beta_{d,t} \cdot Dist_d \cdot Week_t + \lambda_i + \mu_t + \epsilon_{i,d,t} \]

where \( y_{i,d,t} \) indicates logarithm values of foot traffic and sales at block \( i \), in distance \( d \), and week \( t \).9 \( Dist_d \) (\( d=1,\ldots,5 \)) is a dummy variable indicating whether block \( i \) is located within a certain radius from the call center, where \( d \) is assigned as 1 to 5 for blocks if the linear distance from the call center to the blocks is within 100 m, 100–300 m, 300–500 m, 500–700 m, and 700–900 m, respectively. Based on the raw data patterns shown in Fig. A3, we use blocks at the farthest distance (\( d = 5 \)) as the control group, where the linear distance from the call center is 700–900 m. We use the week from March 2 to 8 (\( t=0 \)) as the reference week, a week before the cluster case. \( \lambda_i \) represents block fixed effects, controlling for time-invariant heterogeneity in foot traffic and sales within each block. \( \mu_t \) are week-fixed effects, controlling for common time trends of dependent variables across all blocks. We do not include other control variables because we consider block-fixed effects in the regression equation. Since we investigate short-term changes in the dependent variables over the two months, it is not feasible to include time-varying characteristics at the block level.

The parameter of interests are \( \beta_{d,t,s} \) where \( d=1,\ldots,4 \) and \( t=-4,\ldots,-1,1,\ldots,6 \). The estimated parameter values represent differences in log(foot traffic) and log(sales) in blocks in distance \( d \) relative to those in the control group distance (\( d=5 \)) in week \( t \), compared to the difference between the two distance groups in the reference week. For statistical inference, we calculated standard errors clustered at the block level to account for serial correlations in foot traffic and retail sales.

5. Results

5.1. Effects on foot traffic

Figure 2 reports DID estimates of the impact of the first large-scale COVID-19 cluster on foot traffic in Seoul. Table A110 Panels A and B separately present the findings based on weekdays and weekends to distinguish the role of the business closure order in the cluster building and risk avoidance behavior by the citizens. Foot traffic during weekends is more likely to reflect voluntary decisions because most employees would not need to commute to their workplaces.

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8 1 US$ is equivalent to 1203 Korean Won as of July 20, 2020.
9 We assign the following values to the week variable: -4 to February 3–9, -3 to February 10–16, -2 to February 17–23, -1 to February 24–March 1, 0 to March 2–8, 1 to March 9–15, 2 to March 16–22, 3 to March 23–29, 4 to March 30–April 5, 5 to April 6–12, and 6 to April 13–19.
10 Table A1 reports the corresponding regression results for log(foot traffic) and log(sales) during weekdays.
Panel A reveals limited heterogeneity in trends based on the distance from the cluster before the outbreak, thus providing evidence of a pre-parallel trend assumption that the change in foot traffic over time is similar across distance groups. Furthermore, we observe a sharp decline of 14 and 18% in foot traffic within the cluster’s 100 m (.06 mile) radius during the first and the second week after the outbreak, respectively, which is statistically significant at the 1% level. The foot traffic response within a 100–300 m radius from the cluster records a similar pattern with smaller magnitudes, whereas the estimates during the first two weeks are statistically significant at the 1% level. However, there is no evidence of a decrease in foot traffic beyond a 300 m radius after the outbreak of the call center cluster. The estimates are smaller in magnitude and statistically insignificant. The reduced foot traffic within a 300 m radius starts rebounding after two weeks, consistent with the fact that businesses in the call center building are permitted to operate after two weeks. There is also a possibility of people becoming less cautious about visiting places near the call center cluster after two weeks because the vast majority of the linked cases to the call center cluster were confirmed within a couple of days after the public disclosure of the cluster, and only a few more cases were confirmed after the first week. The reduced foot traffic fully recovers to its pre-outbreak level after four weeks of the outbreak. Our back-of-the-envelope calculation suggests that, over four weeks after the call center cluster outbreak, the number of individuals visiting the area during weekdays reduced by 47.6 and 17.7% within a 100 m and 100–300 m radius, respectively, compared to the average foot traffic during the week just before it. The reduced foot traffic attributed to the outbreak of the Guro call center cluster over the four weeks within a 300 m radius is equivalent to about 0.6% of the average hourly foot traffic of the entire Guro district during the week immediately before the cluster outbreak.

Panel B demonstrates the impact on foot traffic during weekends, indicating little evidence of a decline in foot traffic in the vicinity of the call center building after the cluster outbreak. This result suggests that the risk avoidance behavior of citizens did not play a significant role in reducing foot traffic in response to the cluster outbreak. It is also noteworthy that there is a differential pre-trend within a 100 m radius well before the cluster outbreak. This decrease is possibly attributed to the risk avoidance behavior of individuals because the number of aggregate confirmed cases in South Korea recorded a sharp increase from February 18, 2020, two weeks before the call center cluster outbreak. There are large event venues exclusively used for weddings and a full-fledged hotel also containing large wedding halls in a 100 m radius of the call center building. Since wedding ceremonies usually take place on weekends and involve many guests from various locations, people might have avoided visiting places near the call center building even before the cluster was created.

We conduct the heterogeneity analysis by age to examine potential mechanisms that would cause a decrease in foot traffic in the cluster during weekdays. Since the coronavirus presents a more severe health risk to older adults, existing studies have shown that the elderly have a stronger incentive to avoid the risk of infection (Argente et al., 2020; Brotherhood et al., 2020). However, the individuals linked to this building were ordered to self-quarantine, and their average age was 38 years (Park et al., 2020). We hypothesize that, if the risk avoidance behavior (the business closure order) is the leading factor, then the impact on foot traffic would be greater among older adults. Panel A of Fig. A4 shows a greater foot traffic impact among younger adults in their 20s and 30s than older adults. This suggests that the influence on foot traffic during week-
Fig. 2. Foot traffic response to the Guro call center cluster. Notes: The dependent variable is the average hourly total foot traffic per week in logarithm. For panels A and B, we use foot traffic data during weekdays and weekends, separately. Lines with symbols indicate DID estimates for each distance group. We calculate standard errors clustered at the block-level and corrected for heteroscedasticity. Light gray dash lines represent 95% confidence intervals.

Days is likely due to the business closures. To further investigate the hypothesis that the reduction in foot traffic is due to business closure, we exploited the fact that 72% of individuals connected to the call center building were females. Panel B of Fig. A4 indicates that the decline in foot traffic is greater among females, which is consistent with our interpretation. Fig. A5

5.2. Effects on sales

Figure 3 presents DID estimates for the total retail sales. The overall trends of sales during weekdays are similar to foot traffic, as shown in Panel A. The total sales decreases by about 140% within a 100 m radius at its peak, which is statistically...
significant at the 1% level. Further, it starts rebounding after two weeks, reaching the pre-outbreak level after four weeks. The sales response within a 100–300 m radius exhibits a similar pattern, but with smaller magnitudes. The estimate is statistically significant at the 1% level at its peak. Our back-of-the-envelope calculation indicates that during the four weeks after the outbreak of the cluster, sales within a 100 m and 100–300 m radius of the cluster reduced by 354 and 258% in total, respectively, compared to the average sales during the week right before the cluster outbreak. The reduction in sales due to the outbreak of the Guro call center cluster over the four weeks within a 300 m radius is equivalent to 1.85% of average daily sales of the entire Guro district during the week just before the cluster outbreak.

Panel B shows limited evidence of systematic changes in sales during weekends. In combination with the findings of Panel B in Fig. 2, this result implies that the cluster did not lead to significant economic costs during weekends because citizens did not display a definite risk avoidance behavior. However, we acknowledge that the pattern of sales within a 100 m radius of the cluster is noisy but appears to decrease following the outbreak of the cluster. We suspect that the noisy pattern is mostly attributed to the change in sales linked to wedding ceremonies.\footnote{We find similar sales reductions in blocks where other wedding venues are located during the pre-cluster period.} Since a wedding ceremony in South
Korea typically involves huge expenditures, a massive wedding ceremony can significantly affect the sales patterns within a limited geographical boundary (i.e., only one block within a 100 m radius) significantly.\(^\text{13}\)

The heterogeneous sales impact by sector is further investigated in Fig. 4 to examine whether sectors with more discretionary consumer spending face a larger reduction in sales. Considering that the baseline impact on sales is observed only within a 300 m radius of the cluster, we modify our baseline DID model to estimate changes in retail sales between blocks within a 300 m and 300–900 m radius of the cluster before and after the outbreak in each sector. Each bar represents the DID estimates of the total sales during weekdays within a 300 m radius during the first two weeks after the outbreak, compared to a 300–900 m radius. This indicates that sales reduction by relatively discretionary spending items. For example, a larger decline in sales is observed in the apparel and accessories sector (-279%) and the sports/entertainment sector (-202%) compared to the restaurant or healthcare sectors.\(^\text{14}\)

We further conduct a heterogeneity analysis by age and gender to examine potential mechanisms. Fig. A6 shows that the estimated impact on sales is generally greater among younger individuals and females, which is consistent with the findings in Fig. A4. The results imply that sales reductions are primarily driven by businesses’ closures in the cluster building rather than risk avoidance behavior.\(^\text{15}\)

5.3. Foot traffic and sales responses to the Itaewon cluster

South Korea has successfully managed the COVID-19 situation without having large-scale waves and large-scale lockdowns. However, there were other localized COVID-19 clusters following the Guro call center case. Individuals’ responses to other clusters could have differed because the Guro call center cluster received much media coverage. We partially discuss the external validity of our baseline findings by studying foot traffic and sales responses to the outbreak of another large COVID-19 cluster in Itaewon, a neighborhood of high-density entertainment outlets in Seoul. Consistent with the fact that Itaewon is a highly concentrated entertainment area, Table A2 shows that foot-traffic and sales amounts around the cluster are greater than those around the Guro call center.

The first case from the Itaewon cluster was confirmed on May 7, 2020, approximately two months after the Guro call center cluster.\(^\text{Fig. A8}\)\(^\text{16}\) On May 9, 2020, after confirming more than 15 cases, the Mayor of Seoul declared an administrative order to ban gathering only at specific entertainment outlets such as night clubs and lounges in Seoul. Unlike the business

\(^\text{13}\) Although weddings are planned ahead of ceremony dates, paying costs of weddings on the day of the ceremony is a social norm in South Korea.

\(^\text{14}\) Fig. A7 shows the results of the same analysis using weekend data. Apparel and accessories (-150%), sports/entertainment (-77%), event/home service (-165%), and car sales/car service (-125%) show a significant decrease.

\(^\text{15}\) Hypermarkets and a large-scale department store are located within a 500–900 m radius from the cluster. Risk-averse individuals may shun these places to avoid crowds after the call center cluster outbreak. We use a modified DID model to estimate the effects of the cluster on sales in these places compared to change in sales in other blocks within the same distance group. There is limited evidence of the outbreak at the call center cluster causing a reduction in sales at hypermarkets and the department store, suggesting that citizens’ risk avoidance behavior may not manifest in significant economic costs.

\(^\text{16}\) Fig. A8 shows that the location of Itaewon cluster is located near two subway stations (Itaewon and Noksapyeong) and surrounded by the government-designated tourism area (in Korean).
closure introduced during the Guro cluster, this gathering ban lasted until October 12th, 2020.\textsuperscript{17} The number of confirmed cases sharply increased since its first case, and the total number of confirmed cases was 269 individuals (including 139 Seoul residents), larger than that of the Guro call center cluster. Fig. A9 shows the trend of confirmed COVID-19 cases connected to the Itaewon cluster. Consequently, the media covered the situation closely, and the general public learned about the Itaewon cluster almost immediately. Following the public announcement of the cluster, the number of news articles and keyword searches for the Itaewon case surged on Google and the most popular web search engine (NAVER) in South Korea, as shown in Fig. A10.

We examine the effects of the Itaewon cluster on foot traffic and retail sales by using the same data and the regression specification as in the baseline analysis of the Guro call center cluster. Panel A of Fig. 5 shows foot traffic responses to the Itaewon cluster during weekdays and weekends, indicating sharp declines in foot traffic within nearby blocks after the outbreak.\textsuperscript{18} Foot traffic responses during weekdays sharply rebounded in the following weeks. However, unlike our baseline findings, foot traffic during weekends did not rebound to its pre-cluster level, at least within six weeks. Panel B presents retail sales responses to the cluster during weekdays and weekends, indicating that retail sales in nearby blocks sharply reduced after the outbreak and did not rebound to the pre-cluster level.

Unlike foot traffic and sales responses to the call center cluster, Fig. 5 shows that the Itaewon cluster was associated with persistent reductions in foot traffic and retail sales. Figure A11\textsuperscript{19} We argue that the different results

\textsuperscript{17} It was lifted as the Korean government relaxed the social distancing rules to its lowest level after the pandemic.

\textsuperscript{18} The foot traffic response during weekdays reduced sharply in week 2 (not week 1), as the Mayor of the Seoul Metropolitan government declared the Itaewon cluster on Friday of week 1.

\textsuperscript{19} Fig. A11 presents heterogeneous effects of the Itaewon club cluster by sector, age groups, and gender in Panels A, B, and C, respectively. Panel A indicates that the largest reduction in sales is observed in the restaurant sector and the apparel and accessories sector. The result is similar to those of
between the two clusters might be due to heterogeneity in underlying geographical characteristics. Itaewon is a neighborhood characterized by high-density entertainment outlets, implying a higher risk of infection via personal interactions. This can discourage risk-averse individuals from visiting Itaewon after the outbreak, making the adverse economic impacts of the COVID-19 cluster more persistent. Combined with our baseline findings, this case study could provide a useful insight such that the adverse economic impacts of COVID-19 clusters can be heterogeneous by underlying geographical characteristics Fig. A1220.

6. Conclusion

We estimate the economic impact of the Korean government’s targeted responses to the first large-scale COVID-19 clusters in Seoul. We demonstrate that their economic costs, measured by foot traffic and retail sales, are heterogeneous by the underlying geographical characteristics. The economic costs of a cluster in a highly concentrated business area (Guro) was highly local and temporary. The decline in foot traffic and retail sales were only observed within a 300 m (0.19 mile) radius from the cluster and recorded a full recovery after four weeks. However, the adverse economic impacts of another outbreak of the COVID-19 cluster a highly concentrated entertainment area (Itaewon) were persistent. Our heterogeneity analysis indicates that the reductions in foot traffic and retail sales are primarily caused by temporary business closures in the case of Guro call center cluster. However, the persistent adverse economic impact observed in the Itaewon cluster is likely driven by citizens’ risk avoidance behavior.

Our findings imply that the effects of less intense but more targeted COVID-19 interventions, such as pinpointed, temporary closures of businesses, can differ by underlying geographical characteristics. Since several countries are lifting strict social distance measures while the virus is still actively spreading, our findings provide valuable insight for other countries regarding better management of the COVID-19 situation while protecting the economy.

We acknowledge the limitations of this study. First, the external validity of the findings of this study should be taken cautiously. For example, Seoul is one of the most successful metropolitan cities containing COVID-19. Thus, the targeted approach may not work if the local transmission is widespread and uncontrollable. Second, workers from the building housing the call center remained in their homes throughout the two-week business closure, which may have boosted retail sales in their neighborhoods (e.g., food delivery). This implies that our estimates of economic costs can be overestimated. Unfortunately, the data constraint limits tracking individuals’ consumption spending. However, we argue that this potential bias would not pose a significant problem with our key implication. If this is the case, the actual economic costs would be even smaller than our estimates. Lastly, our study focused on the economic consequences of COVID-19 clusters that occurred in the early stages of the pandemic. Since individuals’ risk-avoiding behaviors could have changed as the pandemic has prolonged, the economic costs of a short-term containment policy could differ over time.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendices

A. Appendix figures and tables

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20 The Itaewon cluster, probably because individuals might have avoided personal interactions regardless of the location and nature of the cluster. Although Panel B shows that reductions in foot-traffic and sales were mainly due to younger individuals aged 20–29 and 30–39 years, Panel C presents little evidence of heterogeneity in foot-traffic and sales responses by gender. These patterns could be reconciled by the fact that Itaewon is a highly concentrated entertainment area. The results are distinct from those of the Guro call center cluster because the reductions in foot-traffic and sales are mainly due to younger female individuals, reflecting the fact that the call center mainly hires younger female workers.

20 We also examined foot traffic and retail sales responses to the media coverage on workers’ interactions with confirmed individuals in other business districts. Compared with the Guro call center case, there was no business closure ordered by the Seoul metropolitan government because there were no or only a few confirmed cases at the time. Fig. A12 shows little evidence that such media coverage reduced foot traffic or retail sales. The results provide additional evidence that the mandated business closure orders are likely to be the main mechanism of adverse economic impacts of COVID-19 clusters.
Fig. A1. Trend of confirmed cases linked to the Guro call center cluster.
Source: Korea Centers for Disease Control and Prevention, Press Release, March 1 – April 10, 2020; Seoul Metropolitan Government, Press Release, March 1 – April 10, 2020.

Fig. A2. Number of news articles and keyword searches containing “Guro call center”.
Notes: Keyword Search Index represents the degree of search interest of the keyword “Guro Call Center” on web search engines in South Korea from March 1, 2020 to April 9, 2020. A value of 100 indicates the peak popularity for the term, a value of 50 means that the term is half as popular, and a score of 0 indicates insufficient search data for this term.
Sources: Google Trends, https://trends.google.com, Naver Datalab, https://datalab.naver.com, Naver News, https://news.naver.com

Fig. A3. Trends of foot traffic and sales by distance to the Guro call center cluster.
Note: The dependent variables are the average hourly total foot traffic and the average daily sales amount during weekdays in logarithm, respectively.
Fig. A4. Foot traffic response to the Guro call center cluster by age and gender.
Table A1
The effects of Guro call center cluster on foot traffic and retail sales.

|                      | Log(Foot Traffic) | Log(Sales) |
|----------------------|-------------------|------------|
|                      | (1)               | (2)        |
| **Radius 0–100 m**   |                   |            |
| × Week -4            | -0.007 (0.012)    | 0.053 (0.121) |
| × Week -3            | 0.022** (0.010)   | 0.059 (0.077) |
| × Week -2            | 0.016 (0.011)     | 0.447*** (0.145) |
| × Week -1            | -0.006 (0.005)    | 0.295* (0.140) |
| × Week 1             | -0.139*** (0.006) | -1.272*** (0.105) |
| × Week 2             | -0.179*** (0.004) | -1.427*** (0.095) |
| × Week 3             | -0.103*** (0.005) | -0.505*** (0.097) |
| × Week 4             | -0.055*** (0.009) | -0.334*** (0.066) |
| × Week 5             | -0.020 (0.014)    | -0.090 (0.082) |
| × Week 6             | -0.041*** (0.015) | -0.302*** (0.074) |
| **Radius 100–300 m** |                   |            |
| × Week -4            | 0.012 (0.021)     | -0.232 (0.217) |
| × Week -3            | 0.042** (0.021)   | -0.092 (0.261) |
| × Week -2            | 0.029 (0.021)     | 0.113 (0.305) |
| × Week -1            | 0.005 (0.009)     | -0.266 (0.368) |
| × Week 1             | -0.058*** (0.011) | -0.986*** (0.373) |
| × Week 2             | -0.065*** (0.016) | -0.564 (0.396) |
| × Week 3             | -0.029* (0.015)   | -0.663 (0.351) |
| × Week 4             | -0.025 (0.020)    | -0.364 (0.336) |
| × Week 5             | -0.021 (0.022)    | -0.188 (0.152) |
| × Week 6             | -0.022 (0.028)    | -0.399 (0.336) |
| **Radius 300–500 m** |                   |            |
| × Week -4            | -0.016 (0.013)    | -0.006 (0.233) |
| × Week -3            | 0.008 (0.013)     | 0.365* (0.203) |
| × Week -2            | 0.001 (0.014)     | 0.224 (0.176) |
| × Week -1            | 0.004 (0.007)     | 0.344 (0.197) |
| × Week 1             | 0.003 (0.007)     | 0.116 (0.254) |
| × Week 2             | 0.014* (0.007)    | 0.138 (0.160) |
| × Week 3             | 0.004 (0.008)     | 0.076 (0.139) |
| × Week 4             | 0.005 (0.015)     | 0.101 (0.232) |
| × Week 5             | -0.015 (0.021)    | 0.003 (0.129) |
| × Week 6             | -0.028 (0.023)    | 0.025 (0.146) |
| **Radius 500–700 m** |                   |            |
| × Week -4            | 0.003 (0.016)     | -0.048 (0.163) |
| × Week -3            | 0.010 (0.014)     | -0.094 (0.141) |
| × Week -2            | 0.003 (0.016)     | 0.026 (0.202) |
| × Week -1            | 0.011* (0.006)    | 0.033 (0.209) |
| × Week 1             | 0.001 (0.009)     | -0.168 (0.159) |
| × Week 2             | -0.001 (0.010)    | -0.199 (0.192) |
| × Week 3             | 0.000 (0.012)     | -0.134 (0.163) |
| × Week 4             | -0.009 (0.018)    | -0.098 (0.106) |
| × Week 5             | -0.028 (0.021)    | -0.073 (0.170) |
| × Week 6             | -0.034 (0.023)    | -0.040 (0.128) |

Observations: 1353
R-squared: 0.998

Notes: The dependent variables are the average hourly total foot traffic per week and the average daily sales amount in logarithm during weekdays, respectively. Block fixed effect is included. We calculate standard errors clustered at the block-level and corrected for heteroskedasticity.

** p < 0.01,
*** p < 0.05, and
* p < 0.1.
Table A2
Summary statistics of the Itaewon club cluster.

|                    | Average Hourly Foot Traffic per Block Mean (SD) | Average Daily Sales per Block Mean (SD) |
|--------------------|-----------------------------------------------|----------------------------------------|
| Total              | 619 (408)                                     | 16.35 (28.77)                           |
| By Radius:         |                                               |                                        |
| 0–100 m            | 1005 (83)                                     | 58.20 (21.86)                           |
| 100–300 m          | 733 (159)                                     | 27.38 (28.84)                           |
| 300–500 m          | 795 (440)                                     | 5.53 (5.69)                             |
| 500–700 m          | 605 (440)                                     | 19.06 (36.60)                           |
| 700–900 m          | 560 (378)                                     | 11.10 (16.39)                           |

Notes: The statistics are calculated using the data from weekdays during April 2020, the month before the Itaewon club cluster outbreak. Retail sales are measured by a million Korean won.

\[ \text{Fig. A5.} \] Foot traffic response to the Guro call center cluster by residential districts.

Notes: The dependent variable is the average hourly total foot traffic during weekdays and weekends in logarithm. In panel A, we use foot traffic data by residential districts (Guro-gu and others). In Panel B, lines with symbols indicate DID estimates for the difference in each week’s foot traffic differences between Guro-gu and other districts evaluated against week 0. We calculate standard errors clustered at the neighborhood (dong)-level and corrected for heteroskedasticity. Light gray dash lines represent 95% confidence intervals.
Fig. A6. Sales response to the Guro call center cluster by age and gender.
Fig. A7. Weekend sales response to the Guro call center cluster by sector.

Fig. A8. Map of Itaewon club cluster.
Source: Naver Maps (2021)
Fig. A9. Trend of confirmed cases linked to the Itaewon club cluster.
Source: Korea Centers for Disease Control and Prevention, Press Release, May 1 – June 9, 2020; Seoul Metropolitan Government, Press Release, May 1 – June 9, 2020.

Fig. A10. Number of news articles and keyword searches containing “Itaewon club”.
Notes: In Panel A, the number of news articles that can be searched is capped at 4000 by the Internet search engines. Keyword Search Index in Panel B represents the degree of search interest of the keyword “Itaewon club” on the Internet search engines in South Korea from May 1, 2020 to June 1, 2020. The index value of 100 indicates the peak popularity for the term, 50 indicates that the term is half as popular, and the value of 0 indicates insufficient search data for this search word.
Sources: Google Trends (https://trends.google.com), Naver Datalab (https://datalab.naver.com)
A. Sales response by sector

![Graph showing sales response by sector.](image)

**Fig. A11.** Heterogeneous Effects of Itaewon club cluster.  
Notes: In panel A, the dependent variable is the average daily sales amount during weekdays in logarithm. We compare changes in outcomes of interests between blocks within a 300 m radius and 300–900 m radius of the cluster. Each bar represents the DID estimates in the first two weeks after the outbreak. We calculate standard errors clustered at the block-level and corrected for heteroskedasticity. Caps indicate 95% confidence intervals. In Panels B and C, the dependent variables are the average hourly total foot traffic during weekdays and the average daily sales amount during weekdays in logarithm. We use foot traffic data for each age and gender group during weekdays. Lines with symbols indicate DID estimates for each distance group. We calculate standard errors clustered at the block-level and corrected for heteroskedasticity. Light gray dash lines represent 95% confidence intervals.
B. Foot-traffic and Sales response by Age group

Foot-traffic responses

20-29

30-39

40-49

50-59

60-69

Fig. A11. Continued
Sales response

Fig. A11. Continued
C. By Gender

Foot-traffic response

Sales response

Fig. A11. Continued
Fig. A12. Foot traffic and retail sales responses to media coverages on interactions with or visits of confirmed persons in other business districts. Notes: The dependent variables are the average hourly total foot traffic in logarithm and the average daily sales amount during in logarithm. Lines with symbols indicate DID estimates for each distance group. We calculate standard errors clustered at the block-level and corrected for heteroskedasticity. Light gray dash lines represent 95% confidence intervals.
B. Korean government’s responses to COVID-19

The Korean government has responded to the COVID-19 situation by meticulous contact tracing and extensive testing. Basic information such as location history of confirmed cases is obtained via an interview by the local health authority where the case has been confirmed. In a scenario where this information is considered insufficient, additional data (mobile phone location, CCTV footages, card transaction records, etc.) are collected and cross-checked with the information acquired from the initial interview.

Information about the places visited by a COVID-19 positive patient during the entire period from two days before showing symptoms through the beginning of the quarantine period is publicly disclosed on the official websites of administrative districts visited by the patient so that people can avoid high-risk areas. Furthermore, for each new confirmed case, a text message is sent to district residents notifying them about the availability of contact tracing information of each new confirmed case on the official district website. In the case of the formation of a new cluster instead of a few isolated cases, a joint response team consisting of epidemiological inspectors and other government employees from the KCDC and local governments are quickly mobilized. They conduct thorough epidemiological investigations, and the findings are broadcasted through official daily briefings. The local governments enforced an executive order to temporarily shut down businesses to prevent additional infections only in highly limited circumstances.

Furthermore, the government significantly expanded access to diagnostic tests for detecting COVID-19 cases via walk-through and drive-through screening stations. Since the outbreak of COVID-19, the daily testing capacity has increased almost seven-fold in two months, from 3000 (58 per million) in February 2020 to approximately 20,000 (386 per million) in April 2020. To contain the COVID-19 situation in the quickest possible manner, the Korean government has covered the complete costs of medical treatments for each confirmed patient, as well as the total expenses of diagnostic tests for suspected cases. A suspected case is defined as a person experiencing fever (37.5 °C or higher) or respiratory symptoms (coughs, shortness of breath, etc.) within 14 days of contact with a COVID-19 patient during the symptom-exhibiting period of the patient.

Appendix A

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