Economic Costs of a Social Tragedy: Evidence from the Itaewon Crowd Crush

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Abstract

This study examines the economic consequences of the 2022 Itaewon crowd crush in Seoul, South Korea. The incident led to significant declines in card spending, transaction volumes, and foot traffic in the affected neighborhood; the effects on its adjacent areas were less pronounced. This negative effect persisted over the following two months, though its magnitude gradually decreased. Sector-level analysis shows that tourism-related sectors, such as restaurants and travel, were the primary drivers of reduced card spending, compared with non-discretionary sectors, including education and healthcare. The decline in foot traffic was primarily driven by working-age group, non-local residents, and movements outside regular commuting hours, which may suggest their heightened safety concerns about the incident. These findings provide indicative evidence of consumption reductions tied to shifts in foot traffic, highlighting public safety concerns as a possible mechanism for decreased card spending.

Keywords: Card Spending, Foot traffic, Safety Concerns

JEL Codes: D12, D81, R23

1 Introduction

Safety risks, such as terrorism and natural disasters, pose threats to people's lives and safety. Over the past few decades, there have been some major accidents, such as the 9/11 attacks, the Boston Marathon Bombing, and Hurricane Katrina, that claimed hundreds of people's lives and devastated the victimized area. Given that these events persist and incur unexpected economic costs, it is necessary to investigate the economic consequences of these tragedies.

In this study, I examine how a tragic event that claimed many lives affected the local economy through the case of the Itaewon crowd crush. This event occurred in October 2022 in the Itaewon neighborhood, which is known as one of the major tourist attractions in Seoul, South Korea. When the government lifted pandemic-era restrictions in 2022, a massive influx of visitors to Itaewon on Halloween led to a tragic crowd crush incident. 159 people were killed, and 196 others were injured, and this is the largest mass casualty incident in Seoul since the Sampoong Department Store collapse in 1995.

The Itaewon crowd crush provides a unique environment for two reasons. First, it was an unexpected scale of accident that occurred in the central area of Seoul. The Itaewon area, one of Seoul's representative tourist attractions, experienced an unprecedented large-scale crowd accident crush accident for the first time in Korean history. Second, publicly available data from the Seoul Metropolitan Government provides detailed information on card transactions and foot traffic records. This allows me to explore how people adjusted their economic behavior over time after the tragedy and which factors are the driving forces that contribute to stronger effects.

For the empirical framework, I first analyze how card spending changes after the Itaewon crowd crush using the difference-in-differences (DID) model. I compare the card spending, transaction counts, and foot traffic of the Itaewon neighborhood to those of other neighborhoods in Seoul. Next, I use the event study method to explore the dynamic effects of the Itaewon crowd crush. This main analysis implicitly assumes that the rest of Seoul, excluding

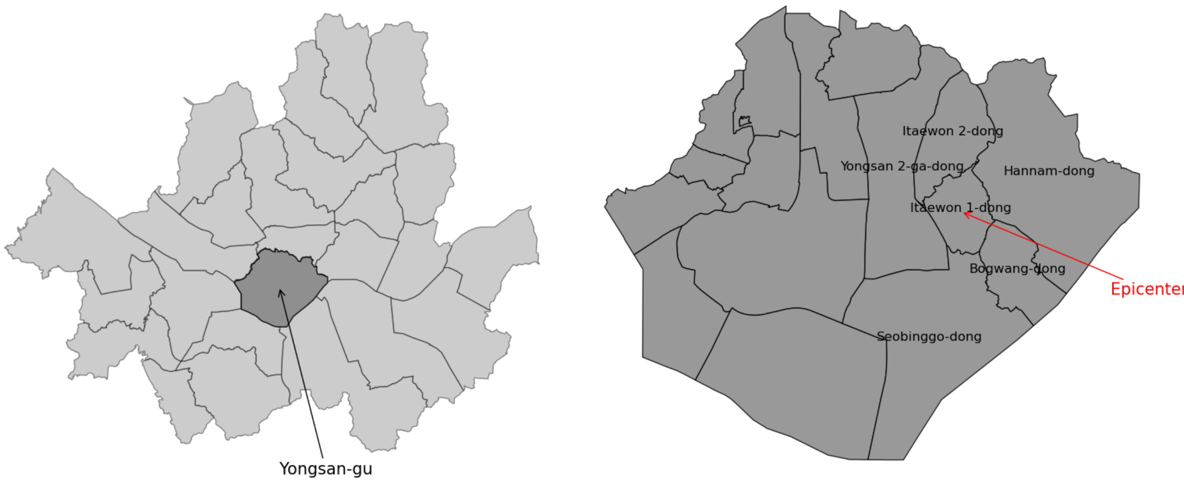


Figure 1: Maps of Seoul and Yongsan-gu

Notes: Seoul city is comprised of 25 administrative districts (referred to as "gu") and 424 neighborhoods (referred to as "dong"). The Itaewon crowd crush occurred in the Itaewon neighborhood (referred to as the Itaewon 1-dong). This neighborhood is surrounded by Itaewon 2-dong, Yongsan 2-ga-dong, Seobinggo-dong, Bogwang-dong, and Hannam-dong.

the Itaewon neighborhood, may have experienced minimal impact from the crowd crush. I estimate the effects by comparing the Itaewon neighborhood with various control groups to validate this assumption. Finally, I implement robustness checks such as permutation tests to verify that the effects are driven by random chance and sensitivity tests following Rambachan and Roth (2023) to address the potential violation of the parallel trends assumption. I also utilize a recently developed method of Arkhangelsky et al. (2021) that addresses the violation of the parallel trends assumption by combining the traits of the DID and the synthetic control-based methods.

The results showed that the Itaewon crowd crush significantly negatively impacted card consumption, transaction counts, and foot traffic in the Itaewon neighborhood. While its magnitude gradually decreased, the negative impact persisted by the end of 2022. On the other hand, adjacent areas of the Itaewon neighborhood experienced less precise impacts, which indicates that the tragic event showed a localized effect. Moreover, there were more pronounced effects on sectors that are relatively more discretionary and related to tourism. Finally, the impact on foot traffic varied significantly by individual traits, with the effects concentrated on the working-age populations, movements outside peak commuting hours, and individuals residing outside of Yongsan-gu, a district where Itaewon neighborhood is located. I also provide test results that validate my findings under possible violations of the parallel trends assumption.

This study contributes several ways to the literature on the economic consequences of tragic events. Previous studies have examined various outcomes such as health status (Andrabi, Daniels and Das, 2023; Akresh, Lucchetti and Thirumurthy, 2012; Levine and McKnight, 2021), emotional well-being (Clark, Doyle and Stancanelli, 2020; Guo and An, 2022; Levine and McKnight, 2021; Soni and Tekin, 2023), educational attainment (Andrabi, Daniels and Das, 2023; Beland and Kim, 2016; Cabral et al., 2021; Levine and McKnight, 2021), and migration (Boustan, Kahn and Rhode, 2012; Deryugina, Kawano and Levitt, 2018; Kim and Lee, 2023; Shakya, Basnet and Paudel, 2022). While these studies provide a broad understanding of the societal impacts of tragic events such as mass shootings, terrorism, and natural disasters, none of them investigated the economic effects of crowd crush.

In terms of economic consequences, prior studies have examined impacts on employment and earnings (Brodeur, 2018; Brodeur and Yousaf, 2022), housing prices (Muñoz-Morales and Singh, 2023; Ratcliffe and von Hinke Kessler Scholder, 2015), and output (Cavallo et al., 2013; Llussá and Tavares, 2011). While studies like Brodeur (2018) and Brodeur and Yousaf (2022) focus on labor market outcomes related to estimating the supply-side effects on local businesses, this research investigates the effects on demand-side variables such as card spending. By uncovering the demand-side mechanisms that influence local economic activity, this study complements existing research that estimates the effects of tragic events on labor market outcomes and offers a more comprehensive understanding of localized economic disruptions.

Moreover, this study examines the impact of these incidents at a local level. While studies such as Llussá and Tavares (2011) analyzed the effects of terrorist attacks on national-level consumption and investment and Cavallo et al. (2013) found the effects of natural disasters on GDP per capita, they do not consider localized impacts where these incident's effects would be most pronounced. In contrast, this study focuses on the immediate and evolving economic effects of a tragedy at the neighborhood level, offering a micro-level perspective on local business disruptions.

To explain potential mechanisms behind decreased local labor market outcomes, Brodeur (2018) utilized survey data capturing emotional factors such as consumer pessimism and safety concerns. However, survey-based responses might be prone to self-report biases and fail to fully represent the severity of emotional and behavioral responses. To address this limitation, this study utilizes foot traffic data, which may directly capture individuals' revealed safety concerns and provide a more accurate reflection of behavioral changes. Additionally, the granular individual-level characteristics in the foot traffic data allow a deeper exploration of the factors driving these behavioral responses.

This research also aligns with studies investigating the economic impacts of government-imposed lockdown policies during COVID-19. Shin, Kim and Koh (2021) investigated the economic effects of targeted lockdowns following a COVID-19 outbreak in the Itaewon neighborhood and reported prolonged negative impacts on card spending in the affected area. On the other hand, Sheridan et al. (2020) utilized a natural experiment comparing Denmark, which imposed social distancing policies during COVID-19, with Sweden, which did not, finding that most economic downturn was caused by the virus itself rather than the restrictions. While these studies investigate the disruptions made by the government, this study focuses on the effect of the unexpected shock on local businesses.

The remainder of this paper is constructed as follows: Section 2 describes the data. Section 3 explains the empirical framework employed in this study. Section 4 presents the empirical results and their interpretations. Finally, Section 5 concludes.

2 Data

I combined data sources of card spending and foot traffic to construct a balanced panel of neighborhood-by-week observations from weeks 17 to 51 in 2022 for all neighborhoods in Seoul, South Korea. I provide more details on each data source below:

2.1 Card Transaction

I use estimates of card transaction data that encompass all offline transaction records in Seoul. This dataset is provided by Shinhan Card, which is Korea's largest credit card company with a 22% market share. The record includes both personal (credit and debit) and corporate card usage for domestic users, while it covers their card usage records for foreign users. Using the record, total card spending and transaction counts in each block are estimated using a methodology that utilizes the company's market share, individual card usage patterns, and other demographic factors.

The data is aggregated at various levels: for domestic users, card spending and transaction counts are compiled for 63 industries at the block level by hour and at the district level by day by gender and age group. The data covers 56 industries for foreign users, aggregated at the block level by hour and district level by country of origin. Certain types of transaction records, such as online transactions, taxes, public charges, telecommunication fees, insurance fees, and university tuition fees for domestic and foreign users, are excluded, with additional exclusions for foreign users, including household services and education fees. For this analysis, I selected domestic user records estimated at the block level by hour.

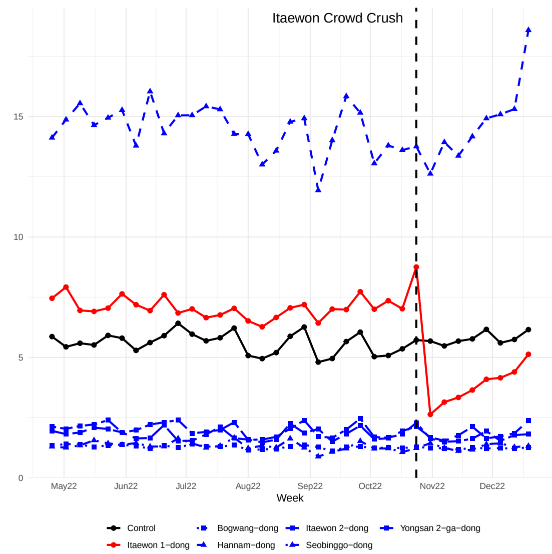
2.2 Foot Traffic

The foot traffic data consists of hourly estimates generated using telephone signal data from KT, the second-largest mobile telecom company in South Korea with a 26% market share. This dataset provides information on both domestic residents and long-term foreign visitors engaged in various activities such as commuting, shopping, and tourism at specific times and locations in Seoul. The data includes demographic details like residential area, gender, and age groups (from 10 to 79 years old, in 5-year intervals). However, to ensure privacy, the dataset does not provide records if the number of people moving by gender/age in a specific hour is less than three. For this analysis, the raw hourly data has been aggregated to a weekly level.

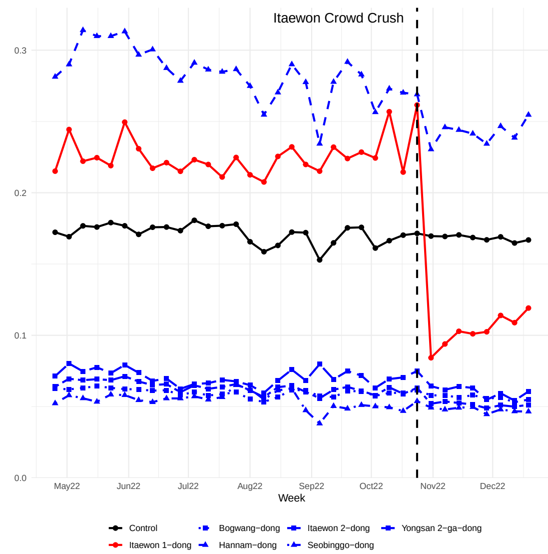
2.3 Descriptive Statistics

Table 1 provides summary statistics for the main variables. The average total card spending per neighborhood in Seoul is KRW 5.622 billion, which is equivalent to approximately US$4.08 million. This indicates that the weekly total spending per neighborhood is 4.08 million dollars. The average transaction count is 170,000, suggesting that, on average, 170,000 card transactions occur per neighborhood each week in Seoul. Finally, the average foot traffic is 1.174 million, implying that 1.174 million people pass through each neighborhood in Seoul weekly.

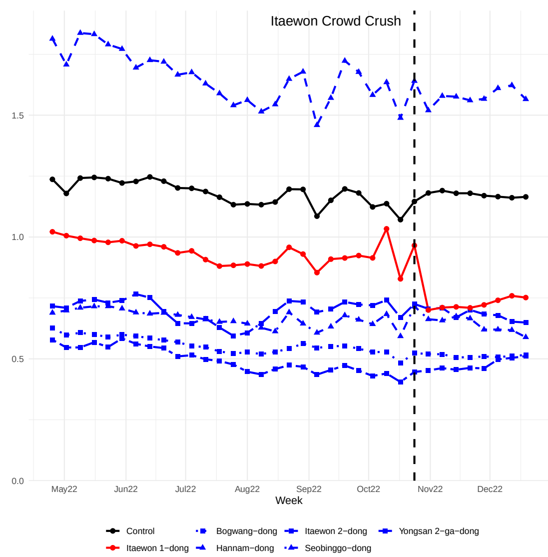
Figure 2 displays the time trend of the main variables for the Itaewon neighborhood (indicated in red), its adjacent neighborhoods (indicated in blue), and the average values of other neighborhoods used as a control group (indicated in black). The vertical dashed line marks the timing of the Itaewon crowd crush in October 2022. After the incident, the Itaewon neighborhood shows a notable decline across all variables, particularly in card spending and transaction counts, with levels failing to recover to pre-incident levels within the given time period. In contrast, the control group's average values remain relatively stable, suggesting that the economic impact may be localized to the affected area. For adjacent neighborhoods, most of them showed minimal changes before and after the incident; in a few cases, slight increases are observed, which might imply positive spillover effects in economic activities to surrounding areas.



(a) Card Spending



(b) Transaction Counts



(c) Foot Traffic

Figure 2: Time Trend of Main Variables

Notes: This figure plots weekly trends of the main variables across the Itaewon neighborhood (red lines), its surrounding areas (blue lines), and a control group (black lines) represented by averaging all other Seoul neighborhoods.

Table 1: Summary Statistics

Variables	Mean	SD	Min	Max
Card Spending	5.622	9.426	0.007	187.643
Transaction Counts	0.170	0.786	0.000	1.687
Foot Traffic	1.173	0.784	0.109	6.707
Observations		14,840		

Notes: Table 1 reports summary statistics of card spending (in billions of KRW), transaction counts (in millions), and foot traffic (in millions) provided by Seoul Metropolitan Government.

3 Empirical Framework

In this study, I investigate the economic effects of the Itaewon crowd crush by using multiple estimation methods. I first assign the Itaewon neighborhood as the treatment unit to identify the economic impact of Itaewon neighborhood, the epicenter of the Itaewon crowd crush. To exclude any spillover effects into adjacent areas, I exclude the five neighborhoods surrounding the Itaewon neighborhood and use the remaining neighborhoods in Seoul as the control group. Next, I define the five adjacent neighborhoods around the Itaewon neighborhood as another treatment group to estimate the effects in the these neighborhoods. This approach allows me to compare the direct impact on the epicenter with the effects on the neighboring areas. For this analysis, the control group includes all other neighborhoods in Seoul, excluding both the Itaewon neighborhood and the adjacent neighborhoods.

3.1 Difference-in-Differences

The main empirical specification in this paper is a two-way fixed-effect (TWFE) difference-in-differences (DID) regression:

$$Y_{it} = \beta \cdot \text{PostTreat}_{it} + \delta_i + \gamma_t + \epsilon_{it} \tag{1}$$

where Y_{it} corresponds to the card spending, transaction counts, and foot traffic of neighborhood i in week t; PostTreat_{it} is an indicator variable equal to one when neighborhood i is a treatment unit and t is after the event and zero otherwise; δ_i is the neighborhood fixed effect; γ_t is the week fixed effect; ϵ_{it} is the error term. The parameter of the interest is the coefficient β. I further include interaction between district dummies and the week dummies in augmented specifications. Throughout the analysis, the standard errors are clustered at neighborhood-level to allow for correlation in units across time.

One of the major concern in this analysis is the potential overestimation of effects due to positive spillovers to other neighborhoods in Seoul. For example, people might have shifted their consumption patterns, avoiding Itaewon and instead preferring to visit its neighboring areas or other major commercial districts within Seoul. To examine this, I take two different approaches. First, I estimate the effects separately for the central area and peripheral area of the Itaewon neighborhood. Using the rest of Seoul's neighborhoods excluding the Itaewon neighborhood and its adjacent neighborhoods as the control group, I compare these neighborhoods with Itaewon neighborhood and its adjacent neighborhoods separately. Next, I utilize three alternative sample comparisons: Itaewon neighborhood versus its adjacent areas, Itaewon neighborhood versus tourist areas[1], and Itaewon neighborhood versus non-tourist areas. This approach allows us to assess the robustness of my findings and confirm any potential spillover effects.

Another concern of this analysis arises when the number of units in a treatment group is small. In this case, clustered-robust standard errors are systematically biased downwards and can result in the over-rejection of the null hypothesis. To address this issue, I conduct permutation tests when the treatment unit is Itaewon neighborhood only. I assign fake treatments to all the other neighborhoods in Seoul except Itaewon neighborhood and five adjacent neighborhoods of Itaewon neighborhood and calculated placebo estimates of β. This allows me to obtain an empirical p-value by calculating a proportion of estimates that have a test statistic greater than that of the estimate in our actual treatment unit.

[1]This includes 24 neighborhoods located in Seoul's major commercial areas.

3.2 Event Study Method

Beyond analyzing the overall impact of the Itaewon crowd crush during the post-treatment period, it may be crucial to measure how the negative shock in the victimized area evolves. To investigate the dynamic effects of the Itaewon crowd crush, I utilize the following event study method estimation model:

$$Y_{it} = \sum_{k=17, k\neq 42}^{51} \beta_k 1[\text{week}_t = k] 1[\text{Treat}_i = 1] + \delta_i + \gamma_t + \epsilon_{it} \tag{2}$$

In the equation (2), $1[\text{week}_t = k]$ denotes 1 if the week number is k and zero otherwise; $1[\text{Treat}_i = 1]$ denotes 1 if a neighborhood i is treated and zero otherwise. I set $t = 42$ as the reference point since the Itaewon crowd crush occurred during week 43.

Moreover, I check the robustness of the estimation results by employing an approach following Rambachan and Roth (2023). I allowed the violation of the parallel trends assumption by bounding the worst-case post-treatment difference in trends into $\bar{M}$ times the equivalent maximum value in the pre-treatment period. I also conduct sensitivity tests by calculating 95% confidence intervals for the main estimates under different values of $\bar{M}$. These sensitivity analyses help assess the robustness of the results when the parallel trends assumption is relaxed and identify the breakdown value of $\bar{M}$, where the null hypothesis can no longer be rejected.

3.3 Synthetic Difference-in-Differences

Another stream of approach to overcome the potential violation of the parallel trends assumption is synthetic control (SC) based methods, proposed by Abadie and Gardeazabal (2003) and Abadie, Diamond and Hainmueller (2010). While these methods can flexibly weight control units to match their pre-exposure trends to those of the treated, they are susceptible to time-varying unobserved confounders and have difficulty conducting robust statistical inference.

To mitigate these concerns, Arkhangelsky et al. (2021) propose a novel method called "Synthetic difference-in-differences (SC-DID)" that integrates attractive features of the DID and SC-based approaches. The basic idea is to highlight control units that are on average similar to the treatment unit and time periods that are on average similar to the post-periods. The parameter of interest, $\hat{\beta}_{sdid}$, is estimated using the following optimization equation:

$$(\hat{\beta}_{sdid}, \hat{\mu}, \hat{\delta}, \hat{\gamma}) = \text{argmin}_{\beta,\mu,\delta,\gamma} \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \delta_i - \gamma_t - \beta \cdot \text{PostTreat}_{it})^2 \hat{\omega}_i^{sdid} \hat{\lambda}_t^{sdid} \tag{3}$$

The estimation takes the following procedures: (1) compute a regularization parameter ζ, (2) compute unit-specific weights $\hat{\omega}_i^{sdid}$ via (1), (3) Compute time-specific weights $\hat{\lambda}_t^{sdid}$, (4) compute $\hat{\beta}_{sdid}$ with the equation (3) while using $\hat{\omega}_i^{sdid}$ and $\hat{\lambda}_t^{sdid}$ obtained in steps (2) and (3).

4 Results

In this section, I present the findings on the economic consequences of the Itaewon crowd crush using the empirical framework explained in Section 3. The results are organized to provide the overall effect, dynamic effect, heterogeneous effects on card spending and foot traffic, spillover effects, and additional results as robustness checks.

4.1 Overall Effect

Table 2 shows the overall effect of the Itaewon crowd crush on economic activities during the post-period, estimated by equations (1). Panel A shows the DID estimates for the Itaewon neighborhood, and Panel B shows the DID estimates for adjacent areas of the Itaewon neighborhood. In columns (1), (3), and (5), I include neighborhood and week-fixed effects as a baseline specification. In columns (2), (4), and (6), I added district-by-week fixed effects.

In Panel A, I find a sharp decline in card spending by 45 to 48%, transaction counts by

50 to 56%, and foot traffic by 19% in the Itaewon neighborhood, compared to their average value. All of these results were all statistically significant at the 1% level. In Panel B, I also find a decline in card spending by 5 to 7%, transaction counts by 10 to 20%, and foot traffic by 3% for the adjacent areas of the Itaewon neighborhood, compared to their mean. However, these neighborhoods experienced relatively modest effects compared to the Itaewon neighborhood. Only estimates for card spending were statistically significant at 5% level across all specifications.

The results suggest the Itaewon crowd crush led to substantial localized economic disruption, with the most severe effects concentrated at the epicenter of the incident. In addition, both Ithe taewon neighborhood and its adjacent neighborhoods experienced a greater decrease in card spending and transaction counts compared to the reduction in foot traffic. This implies that while there was a decrease in foot traffic in the Itaewon neighborhood after the incident, there was also an additional reduction in card spending and transactions among those who visited the area after the incident.

4.2 Dynamic Effect

Figure 4 illustrates the dynamic effects of the Itaewon crowd crush in the Itaewon neighborhood and its adjacent areas, estimated by equation (2). Table 8 provides estimation results for all coefficients. The week before the event, week 42, is omitted as a reference point.

In the Itaewon neighborhood, the strongest effect was observed in week 44, one week after the incident. For example, compared to week 42, card spending in week 44 decreased by KRW 4.7 billion (US$3.4 million), which is almost a 74% decline compared to its mean. Right at the same period, transaction counts decreased by 65%, and foot traffic decreased by 25% compared to their means. Although there was a gradual recovery after week 44, the negative effect did not rebound to its original level by week 51. The estimated coefficients for all variables are consistently negative and statistically significant after the incident.

Table 2: Effects of the Itaewon crowd crush in Itaewon neighborhood and its adjacent areas

	Card Spending		Transaction Counts		Foot Traffic	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Itaewon neighborhood						
Estimate (s.e.)	-2.8669***	-3.0748***	-0.1005***	-0.1111***	-0.1742***	-0.1731***
	(0.0573)	(0.2048)	(0.0006)	(0.0067)	(0.0031)	(0.0140)
Number of observations	14,665	14,665	14,665	14,665	14,665	14,665
Pre-incident outcome mean	6.3564	6.3564	0.1977	0.1977	0.8891	0.8891
Effect relative to mean, percent	-45.1018	-48.3734	-50.8624	-56.2088	-19.5926	-19.4702
Panel B. Adjacent areas of Itaewon neighborhood						
Estimate (s.e.)	-0.2162**	-0.4242**	-0.0107*	-0.0213**	-0.0250**	-0.0239
	(0.0852)	(0.2148)	(0.0059)	(0.0090)	(0.0105)	(0.0174)
Number of observations	14,805	14,805	14,805	14,805	14,805	14,805
Pre-incident outcome mean	4.1773	4.1773	0.1030	0.1030	0.8063	0.8063
Effect relative to mean, percent	-5.1759	-7.5467	-10.3921	-20.6507	-3.1023	-2.9673
Fixed Effects						
Neighborhood FE	YES	YES	YES	YES	YES	YES
Week FE	YES	YES	YES	YES	YES	YES
District-Week FE		YES		YES		YES

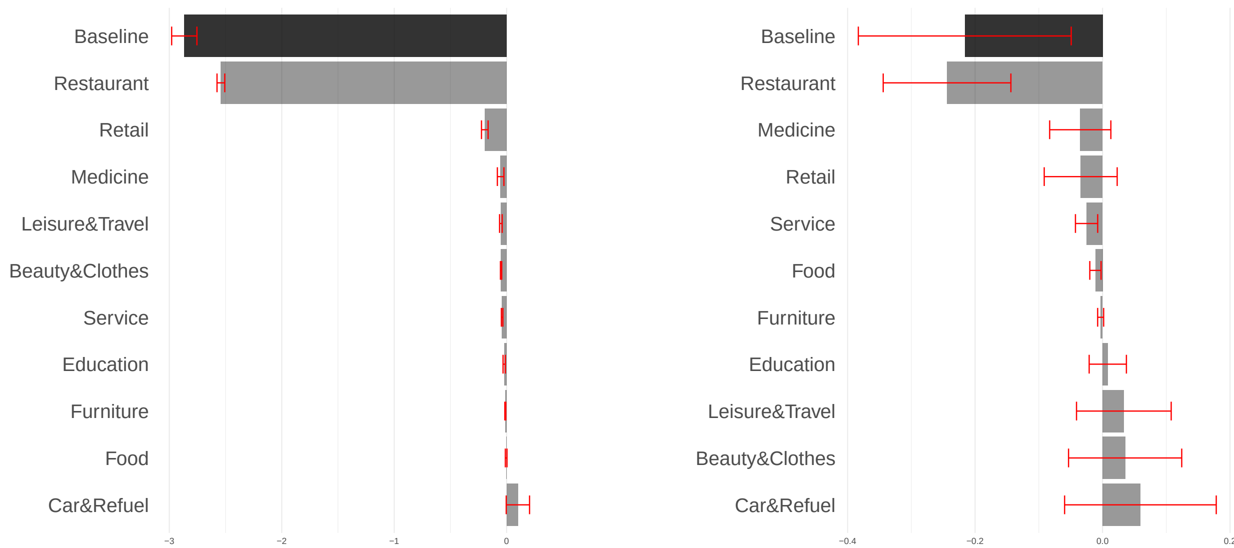
Notes: Estimates of equation (1) from the main text. Standard errors are clustered at the neighborhood level. Pre-incident outcome means are calculated based on the treatment and control group neighborhoods. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

For the adjacent areas of the Itaewon neighborhood, card spending initially showed a negative trend but increased around week 50, though most of these changes were not statistically significant. Transaction counts exhibited negative but statistically insignificant effects, while foot traffic significantly decreased in the first few weeks following the incident.

4.3 Heterogeneous Effects on Card Spending by Consumption Sectors

Figure 3 and Table 9 illustrate the heterogeneous effects of the Itaewon crowd crush on consumer spending across various sectors in both the Itaewon neighborhood (Panel A) and its adjacent areas (Panel B), based on the estimates from equation (1).

In Panel A, the Itaewon neighborhood experienced a decrease in card spending across almost every sector. The most notable declines were seen in sectors closely associated with



(a) Itaewon neighborhood (b) Adjacent areas of Itaewon neighborhood

Figure 3: Card Spending by Sectors

Notes: Estimates of equation (1) of the main text. Caps indicate 95% confidence intervals.

tourism, such as restaurants and leisure&travel sector. For example, card spending in the restaurant sector declined by 155% relative to the pre-incident mean, and card spending in the leisure&travel sector decreased by approximately 77%. On the contrary, less discretionary sectors, such as medical care and food&beverages, showed more resilience. For example, spending in the food&beverages sector saw a minor reduction of 5%.

In Panel B, the adjacent areas exhibited more varied and generally less significant effects across sectors. Similar to the Itaewon neighborhood, the most significant declines were seen in restaurants, with reductions of approximately 14.9% relative to their means, respectively. However, the magnitude of these declines was notably smaller than those observed in the Itaewon neighborhood. In addition, non-discretionary sectors such as medical care and education remained relatively stable, showing no significant impact, which suggests that essential services were largely unaffected outside the immediate vicinity of the Itaewon neighborhood. Unlike the Itaewon neighborhood, however, the leisure&travel sector in the adjacent areas showed a modest increase of 10%, while being statistically insignificant. This implies that the impact of the crowd crush on tourism-related activities was largely concentrated within the Itaewon neighborhood and did not extend as strongly to surrounding areas.

4.4 Heterogeneous Effects on Foot Traffic by Individual Characteristics

Foot traffic data provides hourly information for visitors to specific areas, categorized by age group, sex, and residential district. Utilizing this detailed record, I calculated foot traffic values based on age group, sex, time, and whether movement occurred within or outside the residential district. I then used equation (1) to determine which groups primarily drove the decrease in foot traffic in the Itaewon neighborhood before and after the Itaewon crowd crush.

According to Table 3, the decrease in foot traffic was primarily driven by the working-age population. In Panel A, after the Itaewon crowd crush, weekly foot traffic decreased by approximately 20% for children and 21% for the elderly relative to their means, while the working-age population showed a relatively modest decrease of 9% compared to its mean. These results indicate that the working-age group was the most sensitive to the Itaewon crowd crush, significantly reducing their visits to the area. In terms of absolute magnitude, the working-age population showed a decrease of about 143,400, which accounted for 82% of the overall decrease in foot traffic. This indicates that the working-age population accounted for most of the overall decrease. In Panel B, both males and females showed similar decreases of around 20% compared to the average, indicating a homogeneous response across sexes in terms of avoiding the area.

In Panel C, there was a greater decrease in foot traffic during commute hours than during non-commute hours. Commute hours are defined as the times when an individual arrives at the location between 7 am to 9 am and 6 pm to 8 pm during weekdays. Foot traffic during commute hours decreased by approximately 15%, relative to its mean, while foot traffic during non-commute hours decreased by a larger 21%, relative to its mean. As Commute hour movements can be classified as relatively essential, the smaller decrease in commute

Table 3: Effects of the Itaewon crowd crush in foot traffic of Itaewon neighborhood: By age group, sex, time, and residential location

Panel A: Age group	Children (10-19)	Working age (20-64)	Elderly (65-)
Estimate (s.e)	-0.0078***	-0.1434***	-0.0045***
	(0.0006)	(0.0023)	(0.0004)
Number of observations	14,665	14,665	14,665
Pre-incident outcome mean	0.0393	0.6968	0.0481
Effect relative to mean, percent	-19.6412	-21.1170	-8.7465
Panel B: Sex	Male	Female	
Estimate (s.e)	-0.0726***	-0.0859***	
	(0.0013)	(0.0016)	
Number of observations	14,665	14,665	
Pre-incident outcome mean	0.3798	0.4015	
Effect relative to mean, percent	-19.1104	-21.3883	
Panel C: Time	Commute hours	Non-commute hours	
Estimate (s.e)	-0.0240***	-0.1502***	
	(0.0007)	(0.0025)	
Number of observations	14,665	14,665	
Pre-incident outcome mean	0.1621	0.7270	
Effect relative to mean, percent	-14.7918	-20.6632	
Panel D: Residential Location	Non-local	Local	
Estimate (s.e)	-0.1430***	-0.0312***	
	(0.0019)	(0.0019)	
Number of observations	14,665	14,665	
Pre-incident outcome mean	0.4774	0.4118	
Effect relative to mean, percent	-29.9665	-7.5679	

Notes: Estimates of equation (1) from the main text. Standard errors are clustered at the neighborhood level. Pre-incident outcome means are calculated based on the treatment and control group neighborhoods. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

hour movements compared to non-commute hour movements suggests that people reduced their leisure-related visits.

In Panel D, there was a larger decrease in foot traffic from outside the residential district compared to movement within the residential district. Foot traffic from people living outside the residential district decreased by 29%, relative to the average. In contrast, foot traffic from people within the residential district decreased by only approximately 8%, relative to the average. This suggests that people residing outside Yongsan-gu, the district containing the Itaewon neighborhood, responded more sensitively to the incident than those living within Yongsan-gu.

4.5 Spillover Effects

Table 4: Effects of the Itaewon crowd crush in Itaewon neighborhood using alternative control groups

	Card Spending	Transaction Counts	Foot Traffic
Panel A. Itaewon neighborhood and its adjacent neighborhoods			
Estimate (s.e.)	-2.6506***	-0.0898***	-0.1492***
	(0.0755)	(0.0070)	(0.0120)
Number of observations	210	210	210
Treatment group outcome mean	6.3564	0.1977	0.8891
Effect relative to mean, percent	-41.7003	-45.4464	-16.7794
Panel B. Itaewon neighborhood and tourist areas			
Estimate (s.e.)	-3.7481***	-0.1041***	-0.2193***
	(0.3121)	(0.0064)	(0.0164)
Number of observations	875	875	875
Treatment group outcome mean	6.3564	0.1977	0.8891
Effect relative to mean, percent	-58.9664	-52.6796	-24.6695
Panel C. Itaewon neighborhood and non-tourist areas			
Estimate (s.e.)	-2.8132***	-0.1003***	-0.1715***
	(0.0569)	(0.0005)	(0.0031)
Number of observations	13,825	13,825	13,825
Treatment group outcome mean	6.3564	0.1977	0.8891
Effect relative to mean, percent	-44.2578	-50.7517	-19.2834

Notes: Estimates of equation (1) from the main text. Standard errors are clustered at the neighborhood level. Outcome means are calculated based on the treatment group before the incident. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

To verify whether the main results are sensitive to the choice of the comparison group, Table 4 shows the estimates with different samples. Panel A compares the Itaewon neighborhood with its adjacent areas, which might receive positive spillover effects as people may have shifted their consumption patterns from the Itaewon neighborhood to nearby areas following the crowd crush. However, these magnitudes are smaller by 3 to 4% points than those observed in the main results in Table 2. There was a decline of approximately 41% in card spending, 45% in transaction counts, and 16% in foot traffic, all statistically significant at the 1% level. This result suggests that the adjacent areas may not have absorbed some of the economic activity that would have otherwise occurred in the Itaewon neighborhood.

Panel B compares the Itaewon neighborhood with other tourist areas in Seoul, which could also receive positive spillover effects as consumers shift their behavior. The estimates indicate reductions of 58% in card spending, 53% in transaction counts, and 25% in foot traffic, all statistically significant at the 1% level. While still significant, these estimates are greater in magnitude than the main results, confirming the presence of spillover effects that may have dampened the overall impact observed within the Itaewon neighborhood.

In contrast, Panel C excludes Seoul tourist areas from the control group to mitigate concerns of positive spillovers. The results show declines of approximately 44% in card spending, 50% in transaction counts, and 19% in foot traffic, all statistically significant at the 1% level. These estimates are almost identical to the estimates in Table 2, which confirms that spillover effects on other neighborhoods in Seoul out of the Itaewon neighborhood may be ignorable.

4.6 Robustness Checks

This section examines the robustness of the main results using various tests and alternative methods. Overall, the results support the findings of the main results.

4.6.1 Placebo Tests

In this subsection, I provide the placebo test results obtained by estimating equation (1). I applied a fake treatment to the control group, which included all neighborhoods in Seoul except the Itaewon neighborhood and its five adjacent neighborhoods. This procedure yielded 418 placebo estimates of β. As shown in Figure 5, the estimates for the Itaewon neighborhood demonstrated statistical significance at the 0.05 level for card spending, transaction counts, and foot traffic. This implies that the observed effects are unlikely to be driven by random chance.

4.6.2 Sensitivity Tests

Next, I conduct sensitivity tests following Rambachan and Roth (2023) that allow violation of the parallel trends assumption. This test provides confidence intervals for the coefficient of $k = 44$ in equation (2), which is one week after the Itaewon crowd crush occurred. I tested over different values of $\bar{M} \in [0.5, 2]$, the factor that regulates the maximum deviation of post-trend deviation by which the maximum pre-trend deviation is multiplied. As shown in Figure 6, the sensitivity test results indicate that the findings are robust to violations up to 1.75 times the size of the largest deviation observed in the pre-period, with a "breakdown value" at $\bar{M} = 2$ for card spending and transaction counts. The breakdown value for foot traffic was $\bar{M} = 1$.

4.6.3 Overall Effect estimated by the SC-DID method

Table 5 provides the estimation results using the SC-DID method from equation (3) and compares them with the main results. For the Itaewon neighborhood, the SC-DID estimates reveal substantial economic impacts: card spending decreased by 47%, transaction counts dropped by 45%, and foot traffic declined by 20%, relative to their respective means. The magnitude of these effects is slightly smaller when compared to the DID estimates. These effects are statistically significant at the 1% level, which is consistent with the main results obtained using the DID method.

In contrast, for the adjacent areas of the Itaewon neighborhood, the SC-DID results show less pronounced and, in some cases, statistically insignificant effects. The SC-DID method estimates a 5% decline in transaction counts, significant only at the 10% level, and a 6% reduction in card spending and 3% reduction in foot traffic, both of them being statistically insignificant. These magnitudes are smaller than those reported in the main analysis.

Overall, the SC-DID method produces estimates that support the primary findings in the epicenter of the incident. In contrast, its estimates for the adjacent areas are less pronounced regarding statistical significance and magnitude.

Table 5: Effects of the Itaewon crowd crush in Itaewon neighborhood and its adjacent areas using the SC-DID method

	Card Spending	Transaction Counts	Foot Traffic
Panel A. Itaewon neighborhood			
Estimate (s.e.)	-2.9752***	-0.0906***	-0.1822***
	(0.6479)	(0.0058)	(0.0455)
Number of observations	14,665	14,665	14,665
Pre-incident outcome mean	6.3564	0.1977	0.8891
Effect relative to mean, percent	-46.8064	-45.8270	-20.4926
Panel B. Adjacent areas of Itaewon neighborhood			
Estimate (s.e.)	-0.2679	-0.0056*	-0.0257
	(0.2646)	(0.0030)	(0.0238)
Number of observations	14,805	14,805	14,805
Pre-incident outcome mean	4.1773	0.1030	0.8063
Effect relative to mean, percent	-6.4132	-5.4369	-3.1874

Notes: Estimates of equation (3) from the main text. Pre-incident outcome means are calculated based on the treatment and control group neighborhoods. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

5 Conclusion

This study examined the economic consequences of the Itaewon crowd crush in Seoul, South Korea, utilizing comprehensive card transaction and foot traffic data with detailed consumption sectors and demographic groups. The analysis revealed significant localized economic disruption in the Itaewon neighborhood, evidenced by substantial reductions in card spending, transaction counts, and foot traffic. The effects on the Itaewon neighborhood were most severe immediately after the incident, persisting over the following two months but gradually diminishing in intensity. While adjacent areas also experienced some declines, the impact was less severe, indicating a concentrated economic effect at the incident's epicenter.

The study's findings highlight the vulnerability of certain consumption sectors and demographic groups to such tragic events. For example, tourism-related sectors, particularly restaurants and travel, were most severely affected, while non-discretionary sectors like education and medical care saw less impact. This underscores the sensitivity of discretionary spending to public safety concerns. Furthermore, the analysis of foot traffic data by demographic groups revealed that the working-age population and non-local residents exhibited the most significant decreases in visits, suggesting heightened sensitivity to safety concerns among these groups.

By examining individuals' safety concerns through changes in foot traffic, this research provides indicative evidence of consumption reductions tied to shifts in foot traffic. Overall, this study contributes to understanding the localized economic consequences of tragic events by examining the risk-aversion behavior that influences economic activities and analyzing how economic damages recuperate over time.

6 Appendix

This section extends the analysis from the main text by incorporating a longer time period, from May 2022 to June 2024. This modification addresses a limitation of the initial analysis, which was constrained to identifying effects only within two months following the Itaewon crowd crush. However, due to limitations in the available data, I present this analysis in the appendix. In 2023, as new detailed categories were added or existing classifications were modified for card transaction data, all sectors except the restaurant sector were impacted. Consequently, this analysis focuses exclusively on the restaurant sector's card consumption and transaction volume.

As in the main analysis, I estimate the economic impact on the Itaewon neighborhood, the epicenter of the crowd crush, by designating the Itaewon neighborhood as the treatment unit. To consider potential spillover effects, the control group consists of the remaining neighborhoods in Seoul, excluding those adjacent to the Itaewon neighborhood. I then define these adjacent neighborhoods as a separate treatment group and compare them with the same control group to capture spillover effects in the surrounding areas.

Unlike the main analysis, a government policy was implemented in 2023 to revitalize the local economy of the Itaewon area. In January and March 2023, the Seoul Metropolitan Government issued 1 billion KRW (US$0.75 million) and 3 billion KRW (US$2.25 million) in the form of Seoul Gift Certificates, which were restricted for use within the Itaewon neighborhoods and its adjacent neighborhoods[2]. These certificates were offered at discount rates of 10% and 20%[3], subsidized by the government, to stimulate consumption and support the local economy's recovery. Therefore, this section identifies a "joint treatment" effect, combining the impact of the Itaewon crowd crush and the subsequent government intervention.

I use the following two-way fixed-effect (TWFE) difference-in-differences (DID) equation:

[2]This includes 6 neighborhoods: Itaewon 1-dong, Itaewon 2-dong, Yongsan 2-ga-dong, Seobinggo-dong, Bogwang-dong, and Hannam-dong.

[3]A payback event was later conducted for purchasers of certificates issued at the 10% discount rate during January and February, where 10% of the amount spent was returned in the form of additional gift certificates.

$$Y_{it} = \beta \cdot \text{PostTreat}_{it} + \delta_i + \gamma_t + \epsilon_{it} \tag{4}$$

where Y_{it} indicates card spending in the restaurant sector, transaction counts in the restaurant sector, and foot traffic of neighborhood i in month t.

Table 6 demonstrates the persistent negative economic impact of the Itaewon crowd crush over a significant period, with the effects still evident up to two years after the incident. In Panel A, in the Itaewon neighborhood, card spending in the restaurant sector declined by approximately 34% to 36% relative to the mean, and transaction counts dropped by 30% to 33%. Both results were statistically significant at the 5% level, suggesting that the economic recovery in this area has been sluggish. Foot traffic also declined by about 10.8% compared to the mean, which is consistent with the long-term disruption in local activities. The negative estimates for these variables highlight the long-lasting economic repercussions that were not fully mitigated, even with the government's efforts to encourage spending through Seoul Gift Certificates.

For the adjacent areas of the Itaewon neighborhood, the extended analysis shows a less pronounced effect. In Panel B, card spending in restaurants fell by around 10% to 14%, although these results are not statistically significant. Transaction counts reduced from 4% to 12%, with only a marginal significance observed in one specification. Foot traffic in these adjacent areas demonstrated a slight increase of approximately 2% relative to the mean, indicating that foot traffic may have partially recovered. These findings suggest that while the adjacent areas were initially impacted, their recovery trajectory differs from the core area directly affected by the incident.

To sum up, I confirmed that the card spending patterns in the Itaewon neighborhood closely mirror the results from the main analysis, showing a substantial and sustained decline. However, while the restaurant sector's foot traffic in Itaewon remains below pre-incident levels, there are indications of a gradual recovery trend compared to the initial months following the tragedy. In adjacent areas, although card spending and transaction counts declined,

Table 6: Effects of the Itaewon crowd crush in Itaewon neighborhood and its adjacent areas

	Card Spending (Restaurant)		Transaction Counts (Restaurant)		Foot Traffic	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Itaewon neighborhood						
Estimate (s.e.)	-7.7245**	-7.3858***	-0.2134***	-0.1952***	-0.5271***	-0.5300***
	(0.2259)	(0.7422)	(0.0119)	(0.0414)	(0.0204)	(0.0989)
Number of observations	10,894	10,894	10,894	10,894	10,894	10,894
Pre-incident outcome mean	21.5722	21.5722	0.6462	0.6462	4.0791	4.0791
Effect relative to mean, percent	-35.8079	-34.2375	-33.0254	-30.2084	-12.9211	-12.9929
Panel B. Adjacent areas of Itaewon neighborhood						
Estimate (s.e.)	-1.1411	-0.8024	-0.0260	-0.0078	0.0769	0.0739
	(1.7524)	(1.9399)	(0.0305)	(0.0354)	(0.1100)	(0.1490)
Number of Observations	10,998	10,998	10,998	10,998	10,998	10,998
Pre-incident outcome mean	8.1304	8.1304	0.2110	0.2110	3.5795	3.5795
Effect relative to mean, percent	-14.0354	-9.8687	-12.3414	-3.7142	2.1470	2.0652
Fixed Effects						
Neighborhood FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
District-Month FE		YES		YES		YES

Notes: Estimates of equation (4) from the main text. Standard errors are clustered at the neighborhood level. Pre-incident outcome means are calculated based on the treatment and control group neighborhoods. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

these effects were less pronounced and lacked statistical significance. Foot traffic even showed modest signs of recovery. These observations underscore the need for sustained and targeted policies to ensure the complete economic revitalization of the Itaewon neighborhood and its surrounding areas.

Moreover, to investigate how the economic impacts of the Itaewon crowd crush evolve, I estimate the following event study equation:

$$Y_{it} = \sum_{k \neq -1} \beta_k 1[\text{month}_t = k] 1[\text{Treat}_i = 1] + \delta_i + \gamma_t + \epsilon_{it} \tag{5}$$

with $k = -1$ as the reference point. Figure 7 shows the dynamic impact of the dynamic effects of the Itaewon crowd crush in the Itaewon neighborhood and its adjacent areas, estimated by equation (5).

For the Itaewon neighborhood, the strongest negative effect was observed in the month immediately following the incident. Although there was a gradual recovery across all variables, the negative impact persisted, and the economy did not fully return to its pre-incident levels by June 2024. The estimated coefficients remained consistently negative and statistically significant throughout the period after the incident, indicating a long-lasting impact.

In contrast, for the adjacent areas of the Itaewon neighborhood, aside from a significantly negative effect observed in the month right after the incident, most of the subsequent time periods showed no statistically significant effects. Card spending and transaction counts consistently had negative estimates across all months, but these estimates were not statistically significant for most of the time periods. Foot traffic in these adjacent areas temporarily showed a significant positive effect in September and October 2023, suggesting a brief increase in economic activities.

To sum up, similar to the results in the main text, we can see that the local economy did not return to its pre-incident status. This implies that even in the presence of the governmental aid, the Itaewon neighborhood did not fully recuperate from the shock.

References

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller. 2010. "Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program." *Journal of the American Statistical Association*, 105(490): 493–505.

Abadie, Alberto, and Javier Gardeazabal. 2003. "The economic costs of conflict: A case study of the Basque Country." *American Economic Review*, 93(1): 113–132.

Akresh, Richard, Leonardo Lucchetti, and Harsha Thirumurthy. 2012. "Wars and child health: Evidence from the Eritrean–Ethiopian conflict." *Journal of Development Economics*, 99(2): 330–340.

Andrabi, Tahir, Benjamin Daniels, and Jishnu Das. 2023. "Human capital accumulation and disasters: Evidence from the Pakistan earthquake of 2005." *Journal of Human Resources*, 58(4): 1057–1096.

Arkhangelsky, Dmitry, Susan Athey, David A Hirshberg, Guido W Imbens, and Stefan Wager. 2021. "Synthetic difference-in-differences." *American Economic Review*, 111(12): 4088–4118.

Beland, Louis-Philippe, and Dongwoo Kim. 2016. "The effect of high school shootings on schools and student performance." *Educational Evaluation and Policy Analysis*, 38(1): 113–126.

Boustan, Leah Platt, Matthew E Kahn, and Paul W Rhode. 2012. "Moving to higher ground: Migration response to natural disasters in the early twentieth century." *American Economic Review*, 102(3): 238–244.

Brodeur, Abel. 2018. "The effect of terrorism on employment and consumer sentiment: Evidence from successful and failed terror attacks." *American Economic Journal: Applied Economics*, 10(4): 246–282.

Brodeur, Abel, and Hasin Yousaf. 2022. "On the economic consequences of mass shootings." *Review of Economics and Statistics*, 1–43.

Cabral, Marika, Bokyung Kim, Maya Rossin-Slater, Molly Schnell, and Hannes

Schwandt. 2021. "Trauma at School: The Impacts of Shootings on Students' Human Capital and Economic Outcomes." National Bureau of Economic Research.

Cavallo, Eduardo, Sebastian Galiani, Ilan Noy, and Juan Pantano. 2013. "Catastrophic natural disasters and economic growth." *Review of Economics and Statistics*, 95(5): 1549–1561.

Clark, Andrew E, Orla Doyle, and Elena Stancanelli. 2020. "The impact of terrorism on individual well-being: Evidence from the Boston Marathon bombing." *The Economic Journal*, 130(631): 2065–2104.

Deryugina, Tatyana, Laura Kawano, and Steven Levitt. 2018. "The economic impact of Hurricane Katrina on its victims: Evidence from individual tax returns." *American Economic Journal: Applied Economics*, 10(2): 202–233.

Guo, Shiqi, and Jiafu An. 2022. "Does terrorism make people pessimistic? Evidence from a natural experiment." *Journal of Development Economics*, 155: 102817.

Kim, Hyejin, and Jongkwan Lee. 2023. "Natural disasters, risk and migration: evidence from the 2017 Pohang earthquake in Korea." *Journal of Economic Geography*, 23(5): 1017–1035.

Levine, Phillip B, and Robin McKnight. 2021. "Exposure to a school shooting and subsequent well-being." National Bureau of Economic Research.

Llussá, Fernanda, and José Tavares. 2011. "Which terror at which cost? On the economic consequences of terrorist attacks." *Economics Letters*, 110(1): 52–55.

Muñoz-Morales, Juan, and Ruchi Singh. 2023. "Do school shootings erode property values?" *Regional Science and Urban Economics*, 98: 103852.

Rambachan, Ashesh, and Jonathan Roth. 2023. "A more credible approach to parallel trends." *Review of Economic Studies*, 90(5): 2555–2591.

Ratcliffe, Anita, and Stephanie von Hinke Kessler Scholder. 2015. "The London bombings and racial prejudice: Evidence from the housing and labor market." *Economic Inquiry*, 53(1): 276–293.

Shakya, Shishir, Subuna Basnet, and Jayash Paudel. 2022. "Natural disasters and labor migration: Evidence from Nepal's earthquake." *World Development*, 151: 105748.

Sheridan, Adam, Asger Lau Andersen, Emil Toft Hansen, and Niels Johannesen. 2020. "Social distancing laws cause only small losses of economic activity during the COVID-19 pandemic in Scandinavia." *Proceedings of the National Academy of Sciences*, 117(34): 20468–20473.

Shin, Jinwook, Seonghoon Kim, and Kanghyock Koh. 2021. "Economic impact of targeted government responses to COVID-19: evidence from the large-scale clusters in Seoul." *Journal of Economic Behavior & Organization*, 192: 199–221.

Soni, Aparna, and Erdal Tekin. 2023. "How do mass shootings affect community wellbeing?" *Journal of Human Resources.*

Figures and Tables

Table 7: Consumption sector categories

Sector	Representative categories
Beauty&Clothes	Hair salon, cosmetics, boutiques, clothes, watch shops, and eyeglasses
Car&Refuel	Car sales, car services/goods, and gas
Education	Study room, private cram school, and educational supplies
Food&Beverages	Agricultural and fishery products, butchers
Furniture	Electronics and furniture
Leisure&Travel	Sports activities, movie/play, bookstore, hotels
Medical Care	Hospitals, drugstores, and other medical-related services
Restaurant	Restaurants, bakeries, cafes, and karaoke
Retail	Car sales, car services/goods, and gas
Service	Household services, laundry, work-related services, and interior design

Table 8: Event study method estimates

	Card Spending		Transaction Counts		Foot Traffic	
	Itaewon neighborhood	Adjacent Areas	Itaewon neighborhood	Adjacent Areas	Itaewon neighborhood	Adjacent Areas
Week 43	1.3686***	-0.1578*	0.0458***	0.0020	0.0625***	0.0078
	(0.0689)	(0.0930)	(0.0003)	(0.0013)	(0.0026)	(0.0209)
Week 44	-4.7089***	-0.5327**	-0.1296***	-0.0098	-0.2374***	-0.0653***
	(0.0648)	(0.2092)	(0.0003)	(0.0067)	(0.0040)	(0.0074)
Week 45	-3.9971***	-0.1656	-0.1197***	-0.0069*	-0.2370***	-0.0619***
	(0.1013)	(0.1616)	(0.0004)	(0.0040)	(0.0043)	(0.0098)
Week 46	-4.0024***	-0.4656***	-0.1118***	-0.0082*	-0.2233***	-0.0599***
	(0.1294)	(0.1405)	(0.0004)	(0.0043)	(0.0046)	(0.0156)
Week 47	-3.7876***	-0.2765*	-0.1118***	-0.0068	-0.2272***	-0.0568***
	(0.1057)	(0.1534)	(0.0004)	(0.0049)	(0.0044)	(0.0103)
Week 48	-3.7359***	-0.5176**	-0.1087***	-0.0103**	-0.2053***	-0.0583***
	(0.0818)	(0.2617)	(0.0006)	(0.0055)	(0.0044)	(0.0113)
Week 49	-3.1155***	0.0231	-0.0994***	-0.0078**	-0.1824***	-0.0395*
	(0.1177)	(0.3139)	(0.0005)	(0.0038)	(0.0045)	(0.0203)
Week 50	-3.0112***	-0.0360	-0.1010***	-0.0072	-0.1595***	-0.0360
	(0.1212)	(0.3300)	(0.0007)	(0.0049)	(0.0049)	(0.0250)
Week 51	-2.6888***	0.3412	-0.0920***	-0.0043*	-0.1703***	-0.0553**
	(0.1248)	(0.8732)	(0.0012)	(0.0026)	(0.0055)	(0.0221)

Notes: Estimates of equation (2) from the main text. Standard errors are clustered at the neighborhood level. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Table 9: Effects of the Itaewon crowd crush in Itaewon neighborhood and its adjacent areas by consumption sectors

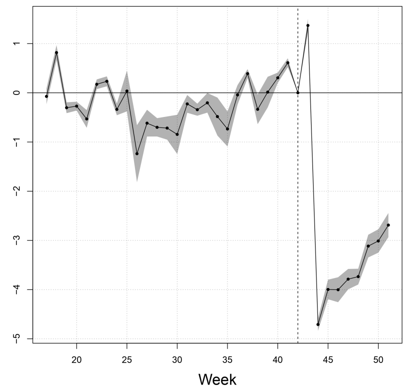
	Beauty&Clothes	Car&Refuel	Education	Food&Beverages	Furniture	Leisure&Travel	Medical Care	Restaurant	Retail	Service
Panel A. Itaewon neighborhood										
Estimate (s.e.)	-0.0494***	0.1002*	-0.0218***	-0.0042	-0.0117***	-0.0511***	-0.0534***	-2.5412***	-0.1941***	-0.0401***
	(0.0029)	(0.0530)	(0.0006)	(0.0038)	(0.0021)	(0.0059)	(0.0149)	(0.0176)	(0.0150)	(0.0035)
Number of observations	14,665	14,665	14,665	14,665	14,665	14,665	14,665	14,665	14,665	14,665
Pre-incident outcome mean	0.2664	0.6033	0.2899	0.1960	0.0803	0.3373	0.8442	1.6390	1.2237	0.1594
Effect relative to mean, percent	-18.5553	16.6053	-7.5145	-2.1511	-15.1624	-76.8709	-6.3282	-155.0420	-15.8616	-25.1307
Panel B. Adjacent areas of Itaewon neighborhood										
Estimate (s.e.)	0.0354	0.0594	0.0082	-0.0112**	-0.0030	0.0334	-0.0350	-0.2440***	-0.0343	-0.0251***
	(0.0453)	(0.0607)	(0.0059)	(0.0045)	(0.0105)	(0.0379)	(0.0245)	(0.0511)	(0.0292)	(0.0089)
Number of observations	14,805	14,805	14,805	14,805	14,805	14,805	14,805	14,805	14,805	14,805
Pre-incident outcome mean	0.2669	0.6010	0.2885	0.1947	0.0798	0.3391	0.8404	1.6347	1.2168	0.1587
Effect relative to mean, percent	13.2729	9.8763	2.8257	-5.7490	-3.7559	9.8413	-4.1651	-14.9237	-2.8153	-15.8203

Notes: Estimates of equation (1) from the main text. Standard errors are clustered at the neighborhood level. Pre-incident outcome means are calculated based on the treatment and control group neighborhoods. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

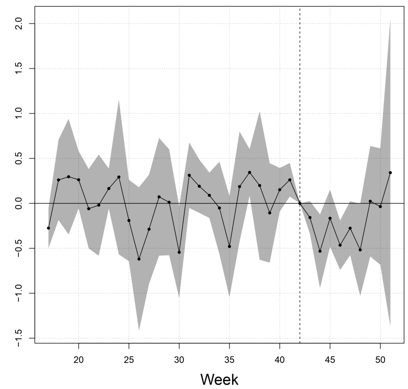
Table 10: Event study method estimates

	Card Spending		Transaction Counts		Foot Traffic	
	Itaewon neighborhood	Adjacent Areas	Itaewon neighborhood	Adjacent Areas	Itaewon neighborhood	Adjacent Areas
October 2022	4.1077***	-0.1998	0.1222***	-0.0027	0.3484***	0.0742*
	(0.3646)	(0.4747)	(0.0018)	(0.0044)	(0.0075)	(0.0388)
November 2022	-17.0603***	-1.8549***	-0.5438***	-0.0476**	-0.9308***	-0.1847***
	(0.1851)	(0.4071)	(0.0025)	(0.0235)	(0.0165)	(0.0551)
December 2022	-12.5659***	-0.7936	-0.4624***	-0.0508***	-0.6925***	-0.1578**
	(0.7522)	(1.7561)	(0.0043)	(0.0138)	(0.0194)	(0.0673)
January 2023	-16.5088***	9.9996	-0.4295***	0.4640	-0.7295***	-0.1029
	(1.5715)	(15.2340)	(0.0355)	(0.4573)	(0.0206)	(0.0731)
February 2023	-17.0752***	5.4389	-0.3935***	0.4600	-0.4792***	0.1215*
	(1.7003)	(12.1588)	(0.0341)	(0.4263)	(0.0185)	(0.0673)
March 2023	-17.7142***	7.2142	-0.4205***	0.5050	-0.6372***	0.0077
	(1.8309)	(13.8747)	(0.0378)	(0.5119)	(0.0182)	(0.0760)
April 2023	-14.2294***	8.1866	-0.3684***	0.4919	-0.4879***	0.0835
	(1.5760)	(14.0160)	(0.0364)	(0.4979)	(0.0198)	(0.1209)
May 2023	-13.9831***	10.5019	-0.3589***	0.4959	-0.5249***	0.0822
	(1.4910)	(14.3017)	(0.0397)	(0.5212)	(0.0199)	(0.0855)
June 2023	-12.7158***	10.5019	-0.3082***	0.5295	-0.4012***	0.0991
	(1.4338)	(14.6620)	(0.0390)	(0.5317)	(0.0203)	(0.0976)
July 2023	-11.5990***	10.3401	-0.2808***	0.5234	-0.3298***	0.0735
	(1.5490)	(14.0399)	(0.0411)	(0.5258)	(0.0217)	(0.1189)
August 2023	-10.8961***	10.3401	-0.2926***	0.5234	-0.3208***	0.0735
	(1.4307)	(14.0399)	(0.0393)	(0.5258)	(0.0213)	(0.1189)
September 2023	-10.8042***	13.1134	-0.2554***	0.5115	-0.3691***	0.2703**
	(1.2346)	(16.8132)	(0.0384)	(0.5176)	(0.0241)	(0.1264)
October 2023	-9.7896***	9.5804	-0.2582***	0.4635	-0.5573***	0.2212**
	(1.4339)	(13.3113)	(0.0410)	(0.4891)	(0.0229)	(0.0956)
November 2023	-13.3821***	10.2333	-0.3540***	0.5061	-0.7259***	0.0299
	(1.6725)	(14.9072)	(0.0401)	(0.5317)	(0.0251)	(0.0645)
December 2023	-10.3866***	10.7315	-0.2626***	0.4365	-0.5053***	0.0344
	(1.2359)	(13.4011)	(0.0416)	(0.4508)	(0.0252)	(0.0882)
January 2024	-13.4663***	10.1879	-0.3161***	0.4835	-0.6957***	-0.0970
	(1.6240)	(15.4497)	(0.0381)	(0.4893)	(0.0257)	(0.0797)
February 2024	-11.3606***	11.2802	-0.2608***	0.4738	-0.4553***	0.0505
	(1.3593)	(15.6237)	(0.0364)	(0.4570)	(0.0261)	(0.1133)
March 2024	-10.3293***	9.9766	-0.2395***	0.4626	-0.5824***	0.0099
	(1.4951)	(14.9698)	(0.0412)	(0.4867)	(0.0239)	(0.1199)
April 2024	-12.2021***	10.8016	-0.3016***	0.4908	-0.8001***	-0.1331
	(1.4388)	(16.2979)	(0.0404)	(0.5344)	(0.0298)	(0.1173)
May 2024	-10.8658***	11.1340	-0.2543***	0.4897	-0.6787***	-0.1012
	(1.4936)	(16.9786)	(0.0430)	(0.5448)	(0.0276)	(0.1259)
June 2024	-8.8837***	11.3977	-0.2039***	0.4943	-0.4168***	-0.0650
	(1.4350)	(16.1037)	(0.0436)	(0.5381)	(0.0270)	(0.1524)

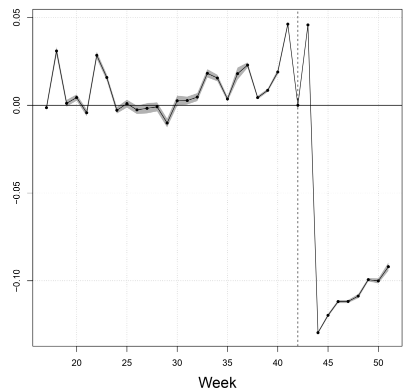
Notes: Estimates of equation (5) from the main text. Standard errors are clustered at the neighborhood level. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.



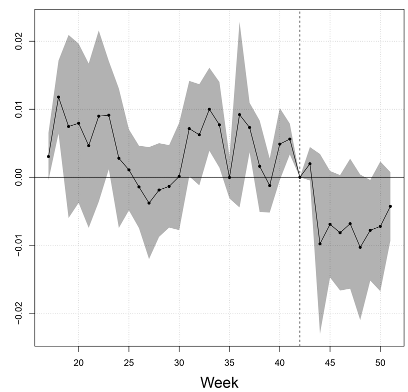
(i) Card Spending



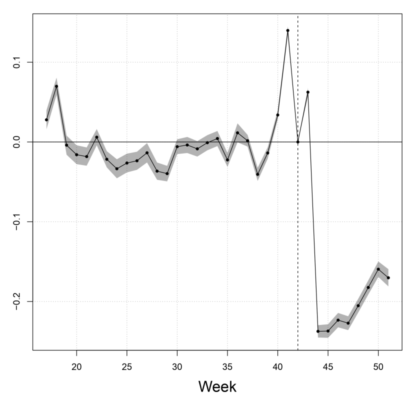
(i) Card Spending



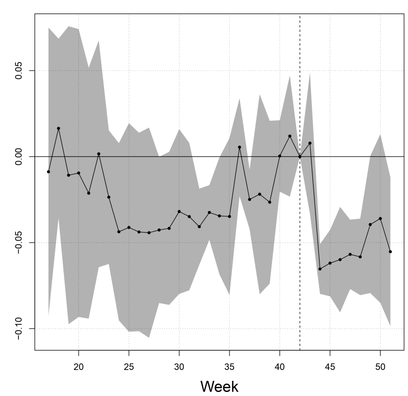
(ii) Transaction Counts



(ii) Transaction Counts



(iii) Foot Traffic



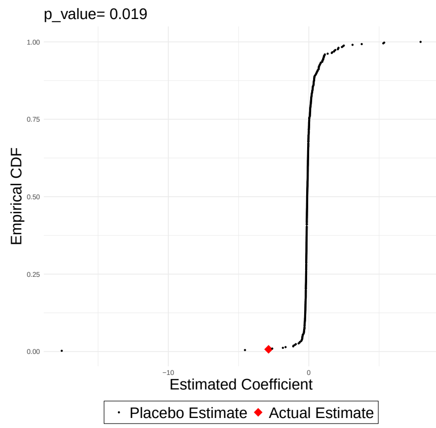
(iii) Foot Traffic

(a) Itaewon neighborhood

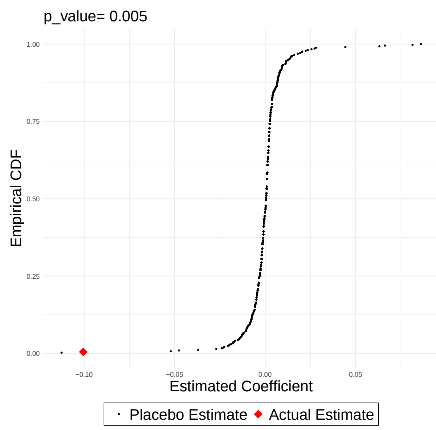
(b) Adjacent areas of Itaewon neighborhood

Figure 4: Dynamic effects of the Itaewon crowd crush

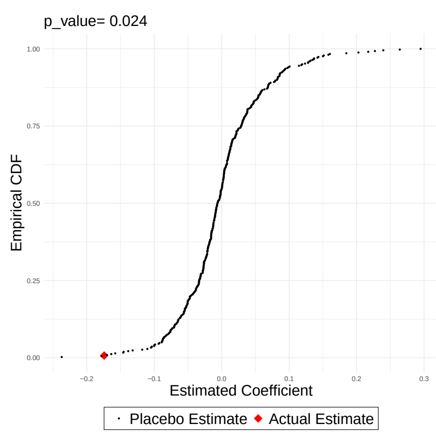
Notes: The figure plots the OLS estimates of equation (2) from the main text. The grey shaded area indicates 95% confidence intervals of each estimate.



(i) Card Spending

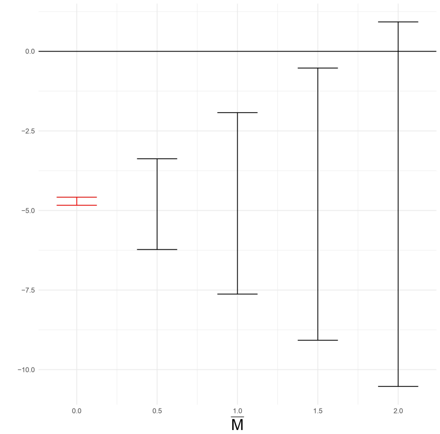


(ii) Transaction Counts

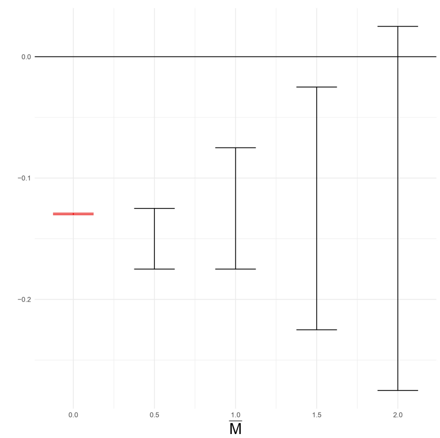


(iii) Foot Traffic

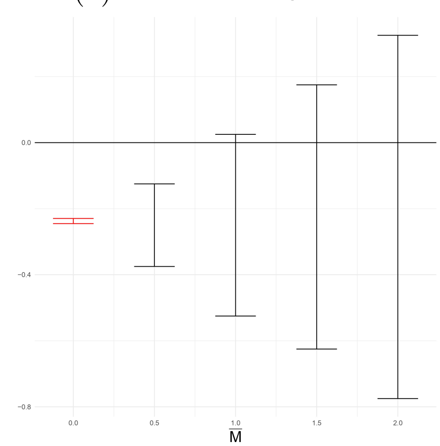
Figure 5: Permutation test for the DID estimates of Itaewon neighborhood



(i) Card Spending

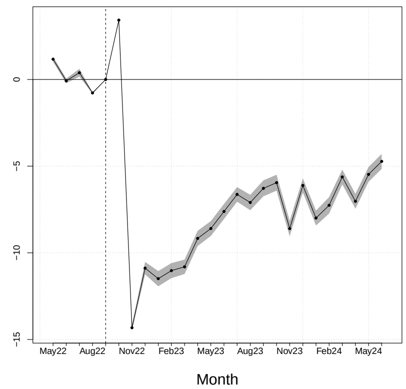


(ii) Transaction Counts

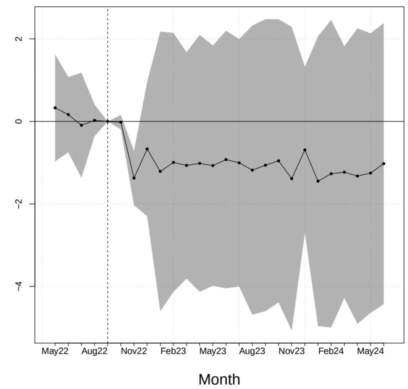


(iii) Foot Traffic

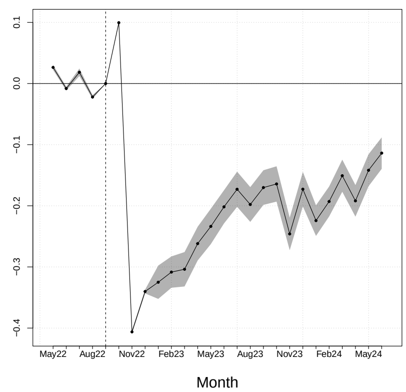
Figure 6: Sensitivity test for the event study method estimates of Itaewon neighborhood



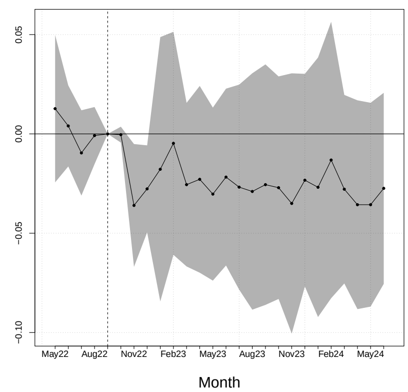
(i) Card Spending (Restaurant)



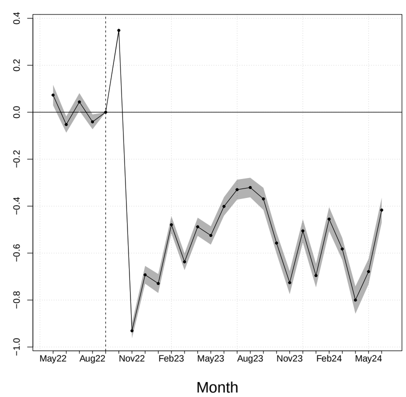
(i) Card Spending (Restaurant)



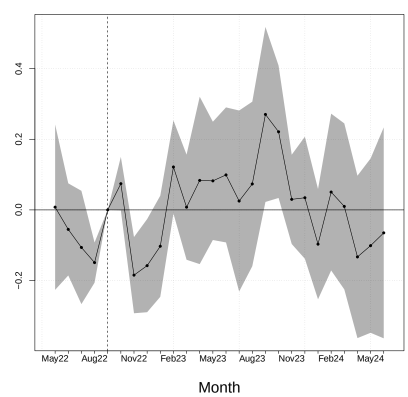
(ii) Transaction Counts (Restaurant)



(ii) Transaction Counts (Restaurant)



(iii) Foot Traffic



(iii) Foot Traffic

(a) Itaewon neighborhood

(b) Adjacent areas of Itaewon neighborhood

Figure 7: Dynamic effects of the Itaewon crowd crush

Notes: The figure plots the OLS estimates of equation (5) from Appendix. The grey shaded area indicates 95% confidence intervals of each estimate.