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Everyone knows what you did: Evidence from public disclosure of COVID-19 and travel logs

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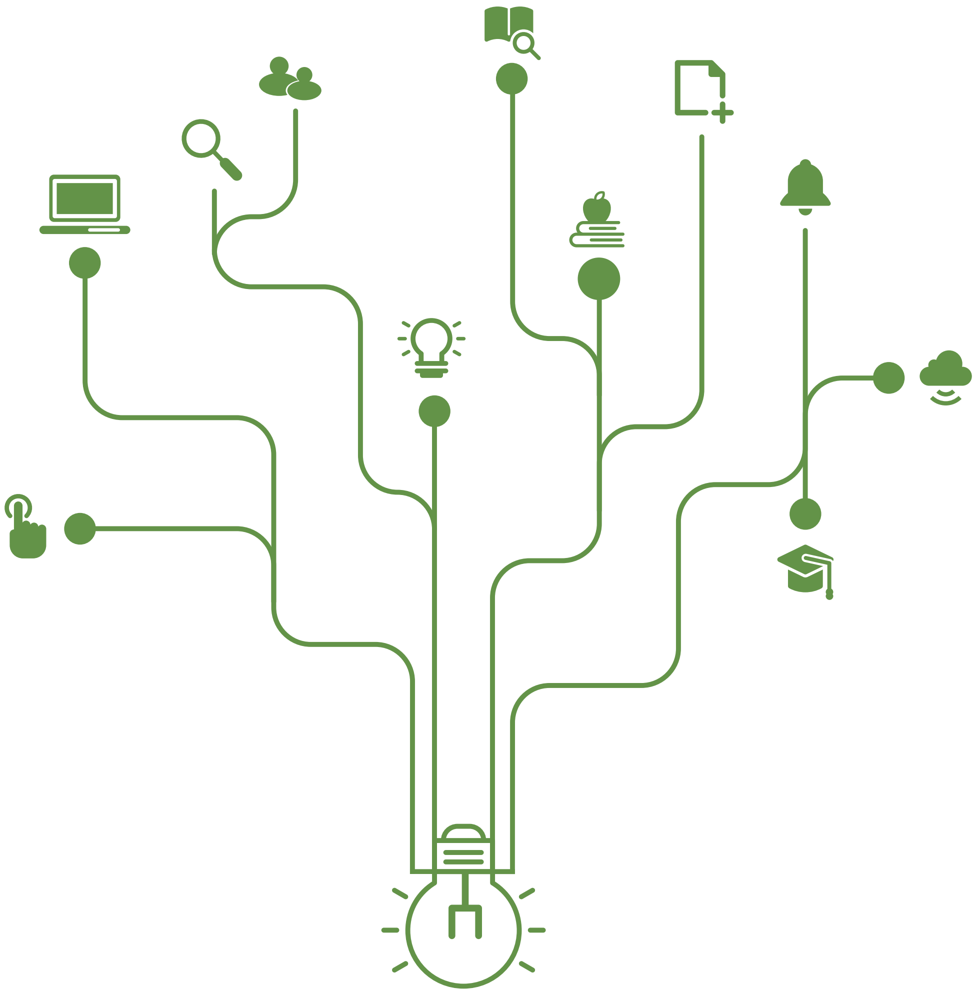

KDI SCHOOL
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Everyone knows what you did: Evidence from public disclosure of COVID-19 and travel logs

Chungeun Yoon*

Abstract

I investigate the effect of public disclosure of detailed location information of people who tested positive for COVID-19 in Seoul. I use data on actual travel logs of people with COVID-19 where they visited before the quarantine, foot traffic from mobile phone signals, consumption spending from card transaction. I find that public disclosure decreased foot traffic and consumption spending for a week in exposure locations and did not increase new confirmed cases in the locations. The results suggest that public disclosure caused economic losses for a short term, but prevented the transmission of infection.

JEL classification: I18, H12, R23

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1 Introduction

The Korean government has conducted contact tracing and testing for those who in close contact in response to a new confirmed case. The local health authority asks a person with COVID-19 to obtain detailed location information where the person visited. The authority also collects mobile phone location, CCTV footages and card transaction data to confirm location history of the person. The travel logs where a person with COVID-19 visited from two days before showing symptoms to the confirmed date are publicly disclosed.

For example, Figure 1 shows that a Korean male, born in 1983, living in Songpa-gu was confirmed on February 5. The website disclosed the places where he visited in the past few days:

- January 30: Stayed at home
- January 31: Went to work at Bungdang-gu using his car. Went to his parents' house at noon. Went back to work at 1pm. Visited to the bakery (Paris Baguette at Helio City) at 7pm. Visited to the store (Kyochon chicken at Garak second store) at 7:15pm. Came home at 11pm
- February 1: Visited to the bakery (Paris Baguette at Helio City) on foot at 9:40am. Visited the hotel in Gangnam-gu (Le Meridien Seoul) at noon using his car. Came home at 3pm. Visited the shopping mall (Hyundai Premium Outlet at Songdo) using his parents' car at 4pm. Went to the restaurant in Songpa-gu (Wongane Kalguksu) at 7:30pm and came home
- February 2: Stayed at home
- February 3: Went to work at Bungdang-gu using his car. Visited the restaurant in Bungdang-gu (Tongyeong Byeolmi) on foot for lunch. Came home
- February 4: Stayed at home
- February 5: Tested positive and transferred to Seoul Medical Center

The information on the travel logs was publicly disclosed on the websites of administrative districts visited by the person. Furthermore, a text message was sent to district residents and those who signed up for the service. Using this information, several websites were created by some developers to share location history on a map incorporated into map applications. Figure 1 shows one of the websites providing travel logs of people with COVID-19.

This paper uses actual travel logs and examines the effect of public disclosure of location information of people with COVID-19. I measure the impact of public disclosure on the transmission of COVID-19 and economic losses measured by foot traffic and consumption spending. Specifically, I collect location information on the date and the geodata (longitude and latitude) from the website based on map applications. I also collect new confirmed cases of COVID-19, floating population from mobile devices and consumption spending from card transaction.

I find that public disclosure (insignificantly) decreased new confirmed cases and decreased foot traffic and consumption spending. I also find that the effects were temporary. Conducting heterogeneous analysis by gender and age, I provide evidence that females and younger adults decreased foot traffic and consumption spending more because of risk avoidance behavior and business closures in response to COVID-19.

To my knowledge, the paper provides the first empirical evidence of the effect of public disclosure of location information. Argente et al. (2021) develops a SIR model about public disclosure in South Korea similar to models of Acemoglu et al. (2021) and Fajgelbaum et al. (2021). They find that public disclosure significantly lowers the number of confirmed cases and the number of deaths, but leads to the economic cost more than that of a lockdown. However, they did not use actual data on public disclosure of location information.

The paper also contributes to a literature on government policy in response to COVID-19. Specifically, previous studies focus on the effects of social distance, lockdown and business disclosure. There is a growing literature using South Korea's case (Shin et al., 2021; Aum et al., 2021b,a) because South Korea has conducted strict government policies to control COVID-19 and provides detailed information on people with COVID-19. However, none of them quantify the effect of public disclosure of location information on people with COVID-19. This paper first investigates the impact of public disclosure using actual travel logs of people with COVID-19, foot traffic measured by mobile phone signals, and consumption spending measured by card transaction data.

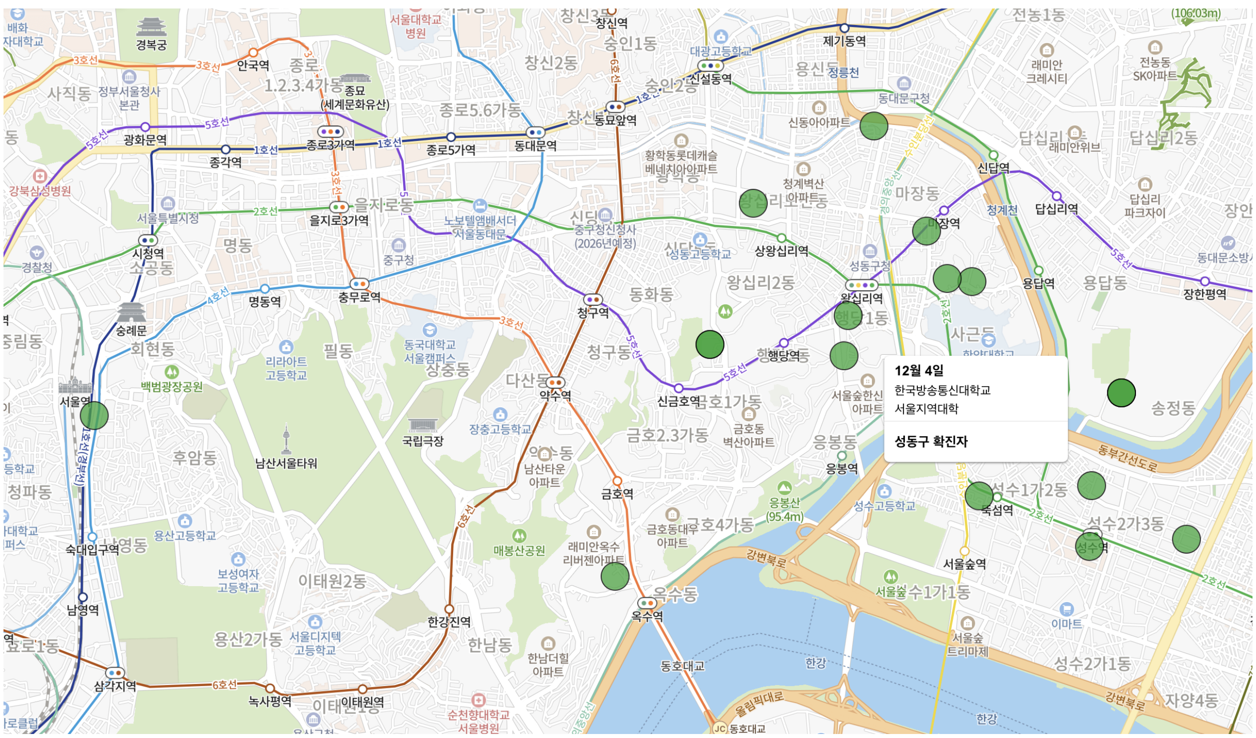
The paper proceeds as follows. Section 2 describes the data and section 3 presents empirical strategy. Section 4 discusses the results. Section 5 concludes.

9 (#19)	한국인 (남, `83)	해외접촉(싱가포르)	2/5	송파구	서울의료원 퇴원

1월 30일 종일 집에 머무름
1월 31일 자차 이용하여 경기도 성남시 분당구 소재 회사 출근, 자차 이용하여 12시경 분당구 소재 부모님 댁 방문, 자차 이용하여 13시경 회사 복귀, 자차 이용하여 19시경 서울시 송파구 소재 빵집(파리바게뜨 헬리오시티) 방문, 19시 15분경 서울시 송파구 소재 음식점(교촌치킨 가락2호점) 방문, 23시경 자택 귀가
2월 1일 도보로 9시 40분경 서울시 송파구 소재 빵집(파리바게뜨 헬리오시티) 방문, 자차 이용하여 12시경 가족 모임 위해 서울시 강남구 소재 호텔(르메르디앙서울) 방문, 15시경 자책 귀가, 16시경 부모님 차량 이용하여 쇼핑몰(현대프리미엄아울렛 송도점) 방문, 부모님 차량 이용하여 19시 30분경 서울시 송파구 소재 음직점(원가네칼국수) 방문 후 자택 귀가
2월 2일 종일 집에 머무름
2월 3일 자차 이용하여 분당구 소재 회사 출근, 도보 이용하여 분당구 소재 음식점(통영별미)방문, 점심식사 후 회사 복귀, 자차 이용하여 자택 복귀
2월 4일 종일 집에 머무름
2월 5일 자택 격리 중 확진 판정 받고 서울의료원 이송

〈출처 : 질병관리본부〉

(a) Example of travel logs



(b) Example of map

Figure 1: TRAVEL LOGS AND MAP

Notes: The first figure shows an example of a person with COVID-19 and travel logs of the person publicly disclosed. The second figure presents an example of a map on the website that shows travel logs of people with COVID-19.

2 Data

2.1 Public disclosures of location information

I collected travel logs from the websites based on map applications such as NAVER map through web scraping. The data allows me to identify a date and a location where a person with COVID-19 visited. Specifically, I extracted the geodata (longitude and latitude) from the website based on map applications. In the website shown in Figure 1, each green bubble presents location information of people with COVID-19 visited. I identified 4,237 location information on date and geodata where people with COVID-19 visited between January and October 2020 in Seoul. In Figure 2, the number of travel logs of people with COVID-19 was shown over time.

The Korean government policy on public disclosure of location information of people with COVID-19 changed over time. There were four major revisions (March 14, April 12, June 30, and October 6, 2020) because of a growing risk of invasion of privacy. The degree of disclosure has shrunk over time.

2.2 COVID-19 cases

I collected daily new confirmed cases from Korea Disease Control and Prevention Agency, formerly Korea Centers for Disease Control (KCDC), and Seoul Metropolitan Government. Figure 3 shows the number of new confirmed cases in Seoul between January and October 2020. I identify the residence at the district level of people with COVID-19 and their gender and age.

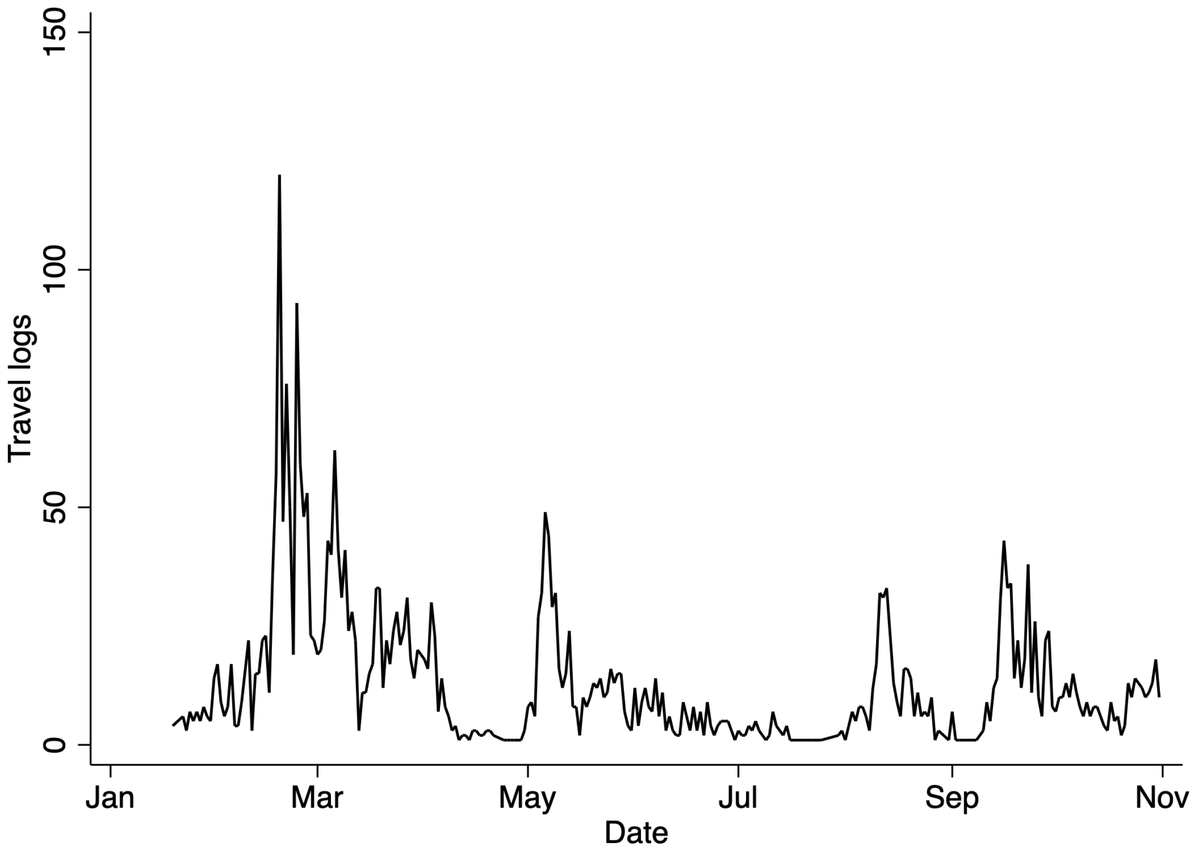


Figure 2: PUBLIC DISCLOSURE OF TRAVEL LOGS

Notes: The figure plots the number of travel logs of those who tested positive for COVID-19 in Seoul. KCDC and Seoul city made contact tracing data of people with COVID-19 public. It covers all cases in Seoul between January and October, 2020.

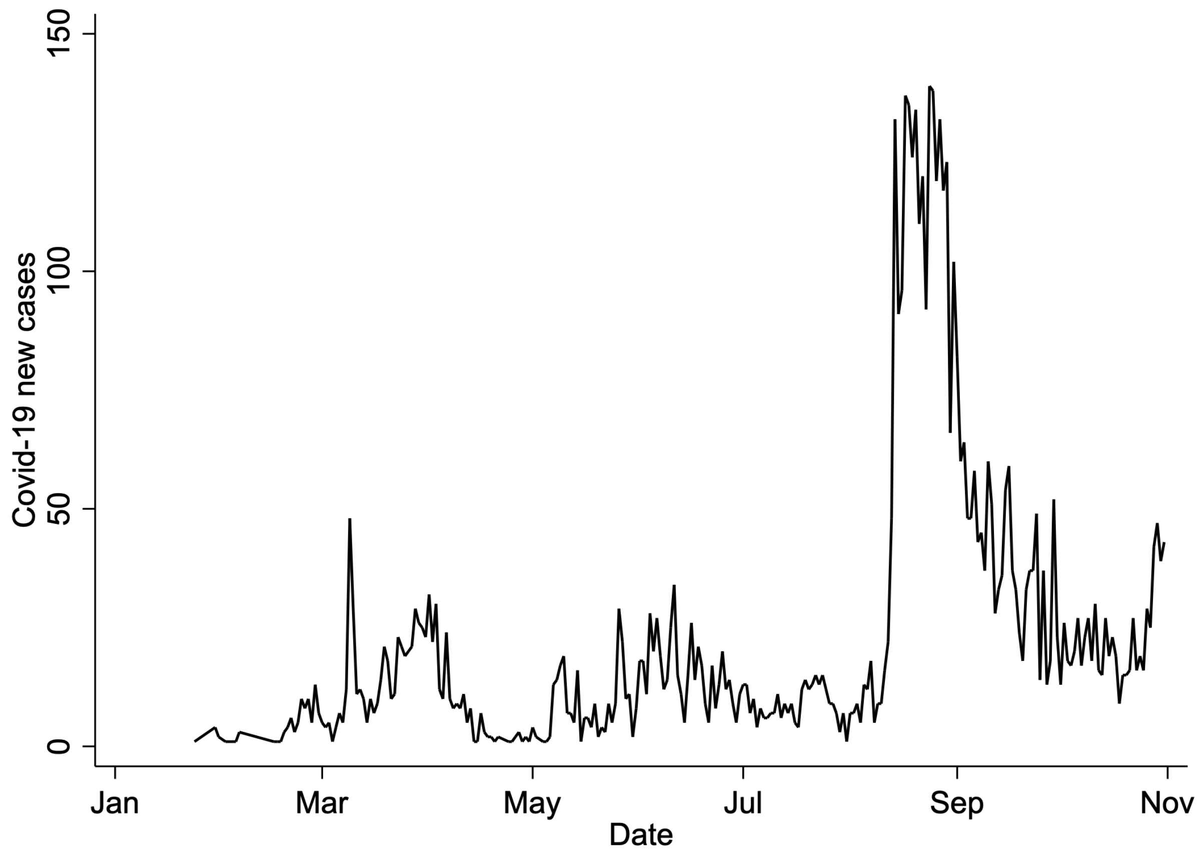


Figure 3: COVID-19 NEW CASES

Notes: The figure plots the number of new confirmed cases of COVID-19 in Seoul. It covers all cases in Seoul between January and October, 2020.

2.3 Foot traffic

I collected foot traffic from the Seoul Open Data Plaza.[1] The Seoul city government estimates the floating population given a specific time and place in Seoul based on mobile phone signals from KT, the mobile telecom carrier with a market share of about 26 percent. Estimates of foot traffic are publicly available. In addition, estimates by gender and age are available. I create panel data on foot traffic at the district level on a weekly basis.

2.4 Card transaction data

To examine consumption pattern analysis, I use card transaction data from the BC card company. The company is the biggest payment processing company in Korea and in alliances with other card companies. The market share accounts for approximately 24 percent and the number of customers is about 36 million people out of 51 million total population in Korea. The data provides spending given a specific date and place by age and gender. I create panel data on spending at the district level on a weekly basis.

2.5 Summary Statistics

Table 1 describes the summary statistics of variables. To investigate the effect of public disclosure of travel logs on outcomes, I create panel data at the district level on a weekly basis. Card transaction data is available during the period between January and October 2020. I use other variables during the same period.

COVID-19 in the first row of the table reports the number of weekly new confirmed cases by district. COVID-19 per million people is divided by district population in millions. Travel logs is the number of weekly travel logs of people who tested positive for COVID-19. Travel logs per thousand people is divided by district population in thousands. I use two main outcomes: floating population in millions from mobile phone signals and consumption

[1] https://data.seoul.go.kr/dataVisual/seoul/seoulLivingPopulation.do

spending in billions from card transaction data. From the 2015 Population and Housing Census, I collect variables used as controls: population, daytime population, and GDP per capita (Gross Regional Domestic Product, GRDP, per capita).

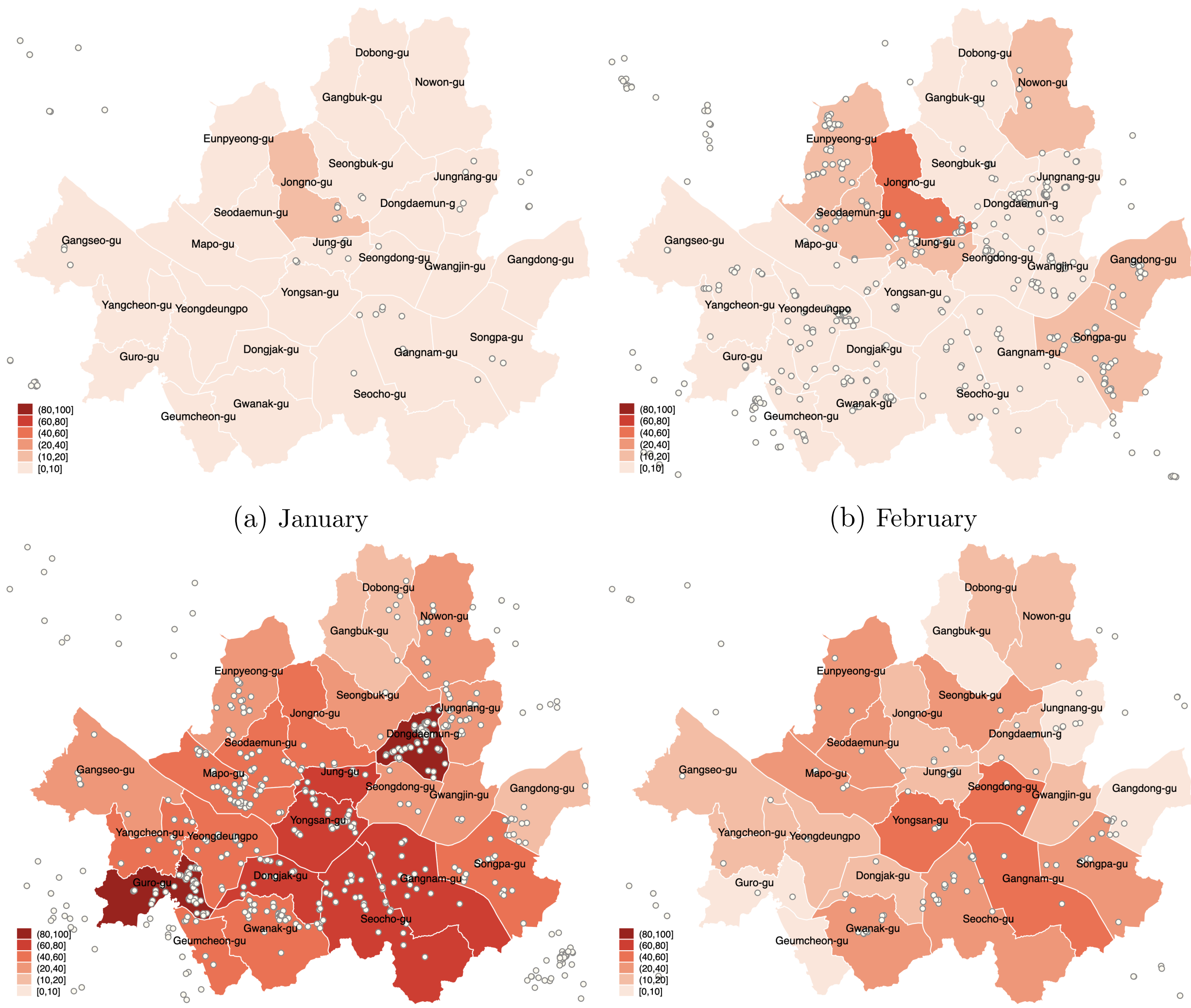
To investigate the effect of public disclosure of travel logs, I first examine the relationship between COVID-19 and travel logs. It is possible that people with COVID-19 moved to any place, but they were more likely to visit the places close to their residence. To be specific, Figure 4 shows the number of COVID-19 new confirmed cases and the travel logs of people with COVID-19 during the first four months from January 2020. A positive relationship between COVID-19 and travel logs is found on the maps. For example, Guro-gu reported a large number of travel logs (bubbles) on March in response to a surge in COVID-19 cases. I investigate this relationship using the regression analysis in the next chapter.

Figure 5 shows the growth rate of floating population and travel logs and Figure 6 presents the growth rate of card transaction. I found a negative relationship between floating population and travel logs and a negative relationship between card transaction and travel logs. I show the regression results in the next chapter.

Table 1: SUMMARY STATISTICS

	Mean (1)	SD (2)	Min. (3)	Max. (4)
A. COVID-19				
COVID-19	5.85	10.24	0.00	138.00
COVID-19 per million people	14.06	22.51	0.00	293.89
Travel logs	3.46	6.97	0.00	70.00
Travel logs per thousand people	0.01	0.02	0.00	0.23
B. Outcomes				
Floating population (in millions)	71.42	23.58	20.51	157.41
Card transaction (in billions)	34.32	48.84	2.82	303.40
C. Characteristics				
Population (in thousands)	411.89	128.77	134.33	667.48
Daytime population (in thousands)	411.33	149.63	248.49	995.04
GDP per capita (in millions)	47.60	75.82	7.29	371.72
Number of districts	25			
Number of observations	2,600			

Notes: The table describes the summary statistics of variables used in the analysis. COVID-19 presents the number of weekly confirmed cases by district. COVID-19 per million people is computed by weekly confirmed cases divided by district population in millions. Travel logs reports the number of weekly travel logs of people with COVID-19. Floating population is collected from weekly foot traffic in millions by mobile devices. Card transaction shows the total amount of weekly card spending in billion won. Population in thousands and daytime population in thousands presents statistics in the year 2015. GDP per capita reports Gross Regional Domestic Product (GRDP) per capita in million won in 2015.

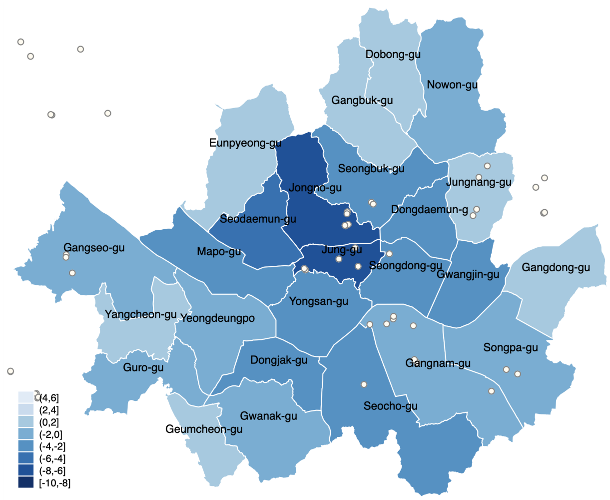


(a) January (b) February

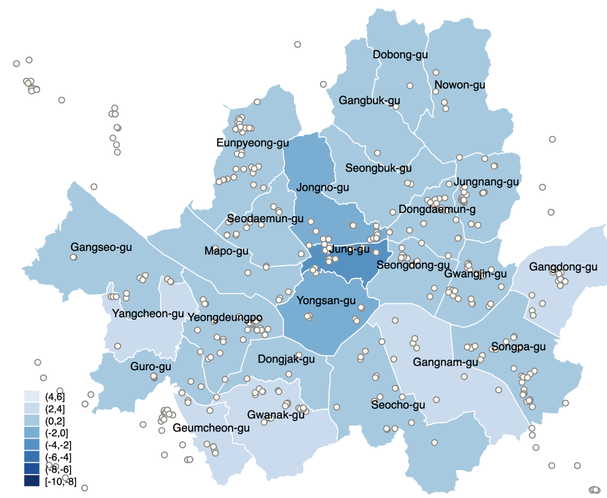
(c) March (d) April

Figure 4: COVID-19 AND TRAVEL LOGS

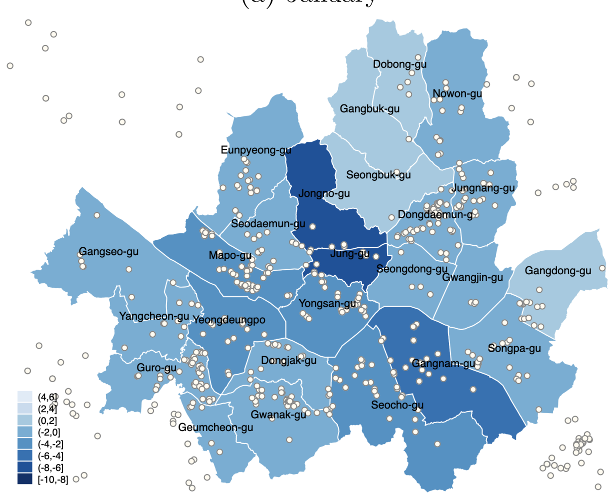
Notes: The figures plot the number of COVID-19 new cases per million population in Seoul. Bubbles show the travel logs of those who tested for COVID-19.



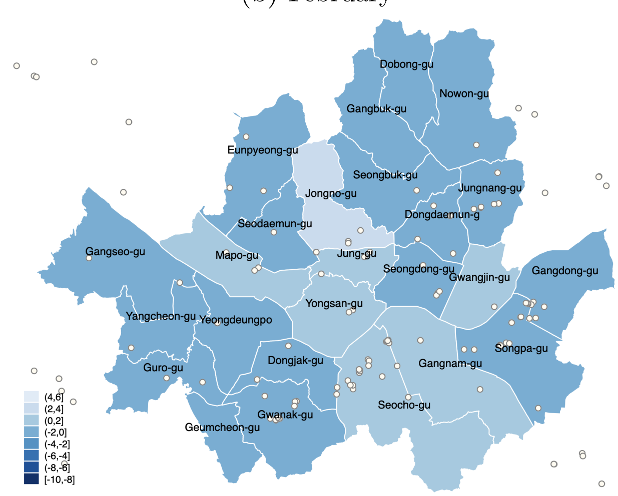
(a) January



(b) February



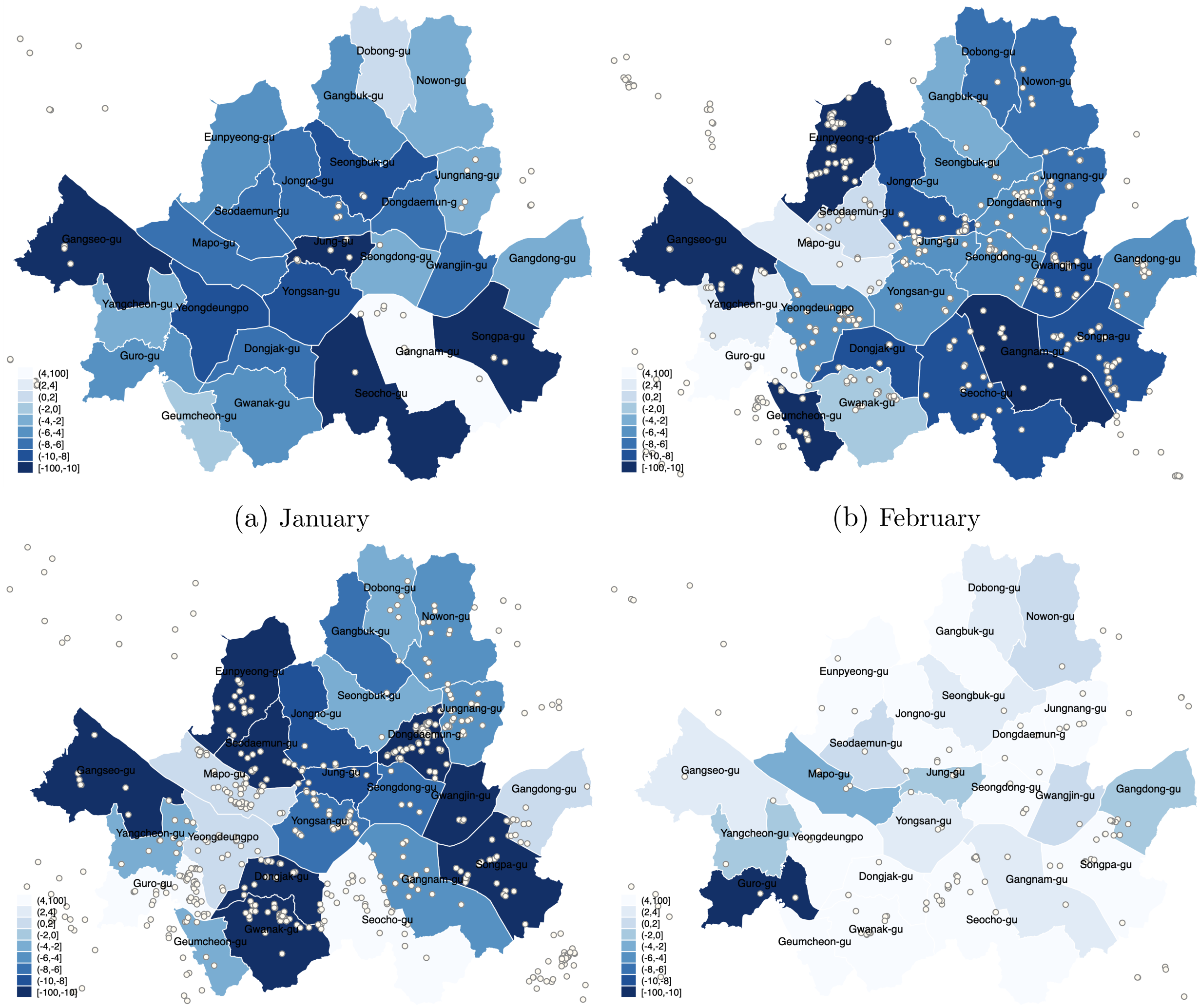
(c) March



(d) April

Figure 5: FLOATING POPULATION AND TRAVEL LOGS

Notes: The figures plot the growth rate of floating population in Seoul. Data represents foot traffic collected from mobile devices. Bubbles show the travel logs of those who tested for COVID-19.



(a) January

(b) February

(c) March

(d) April

Figure 6: CARD TRANSACTION AND TRAVEL LOGS

Notes: The figures plot the growth rate of total amount of monthly card transaction in Seoul. Card transaction data is collected from the BC card company. Bubbles show the travel logs of those who tested for COVID-19.

3 Empirical Strategy

I investigate how public disclosure of travel logs of those who tested positive for COVID-19 prevented the spread of COVID-19 and caused the economic cost. Specifically, I employ the following econometric model:

$$Y_{it} = \beta PublicDisclosure_{it_{+1}} + \gamma_i + \tau_t + \epsilon_{it} \tag{1}$$

Y_{it} is the outcome in district i on week t: COVID-19 weekly confirmed cases per million population in district, log(weekly floating population in millions), and log(weekly card transaction in billions). $PublicDisclosure_{it_{+1}}$ is the number of weekly travel logs per thousand population in district i a week after actual public disclosure on week t. I use 1-week lead public disclosure because new confirm cases on the weekend, Thursday, or Friday affected the current week only partially and most of travel logs were updated a few days after initial public disclosure. District fixed effects γ_i and week fixed effects τ_t are included in the model. Coefficient β measures the effect of public disclosure of travel logs on COVID-19, foot traffic, and consumption spending.

Furthermore, I compare changes in COVID-19, foot traffic, and consumption spending in areas before and after public disclosure of travel logs. I employ the econometric model of a difference-in-differences framework:

$$Y_{it} = \sum_{t=-1}^{2} \beta_t PublicDisclosure_{it} + \gamma_i + \tau_t + \epsilon_{it} \tag{2}$$

$PublicDisclosure_{it}$ is the number of weekly travel logs per thousand population in district i on week t. $PublicDisclosure_{it_{-1}}$ is 1-week lead public disclosure (a week before actual public disclosure), $PublicDisclosure_{it_0}$ is actual public disclosure at t, $PublicDisclosure_{it_{+1}}$ is 1-week lagged public disclosure (a week after actual public disclosure), and $PublicDisclosure_{it_{+2}}$ is 2-week lagged public disclosure (two weeks after actual public disclosure). The key identifying assumption is that outcomes of districts with a large number of travel logs and outcomes of other districts with few travel logs would not change differently in the absence of public disclosure of travel logs.

4 Results

4.1 Effect of public disclosure of travel logs

Table 2 reports regression analysis of the effect of public disclosure of travel logs in Panel A from equation 1 and in Panel B from equation 2. In column 1 of Panel A, I find that public disclosure had no effect on new confirmed cases of COVID-19. In Panel B, it is clear that travel logs on or before public disclosure are positively associated with COVID-19. Because new confirmed cases lead to contact tracing and public disclosure, 1-week lead public disclosure of travel logs and actual public disclosure are positively correlated with COVID-19. However, new confirmed cases did not increase in response to public disclosure. Public disclosure actually controlled new confirmed cases considering that there was a high risk of the transmission of infection. Furthermore, I find a negative effect of 1-week lagged public disclosure on COVID-19 in Panel B. This suggests that new confirmed cases of COVID-19 (insignificantly) decreased a week after public disclosure.

I find that floating population decreased in column 2. Specifically, weekly foot traffic decreased by 16.2 percent a week after public disclosure of 1 weekly travel logs per thousand population in district in Panel A. In Panel B, the results shows that the decrease in floating population did not persist. Two weeks after public disclosure, foot traffic did not decrease significantly.

The results for consumption spending are consistent with those for floating population. In column 3 of Panel A, weekly card spending decreased by 55 percent a week after public disclosure. In Panel B, the decrease in card transaction is found only a week after public disclosure and card transaction did not decrease two weeks later.

Overall, I find public disclosure of travel logs of people with COVID-19 did not increase new confirmed cases of COVID-19 and decreased foot traffic and consumption spending. The effects are found only a week after public disclosure. The results suggest that public disclosure has effect on prevention of transmission of COVID-19, but causes economic costs for a short term.

One concern is that initial differences in districts could lead to the biased estimates. For example, the crowded districts with a high density of population are the better environment for the transmission of COVID-19. It is possible that high daytime population is correlated with high floating population. The level of consumption could be affected by the condition of local economies. To address these issues, I include following controls: population, daytime population, and Gross Regional Domestic Product (GRDP) per capita in the year 2015. Table 3 reports results controlling for time-interacted measures of districts' population, daytime population, and local GDP. The empirical results are robust to controlling for initial differences in districts.

In addition, regression coefficients in panel B of Table 2 are shown in Figure 7. I extend the period to a week before public disclosure and two weeks after public disclosure of travel logs in Figure 8. In case of new confirmed cases of COVID-19, positive coefficients before or on public disclosure suggests that the travel logs of people with COVID-19 are close to their residence. I find no difference between districts in foot traffic and card transaction before public disclosure. This provides evidence on the identifying assumption of parallel pre-trends.

Table 2: THE EFFECT OF PUBLIC DISCLOSURE OF TRAVEL LOGS

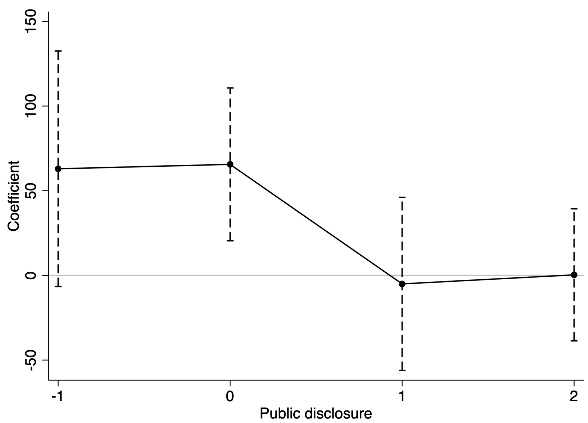
Dependent variable	COVID-19	Floating population	Card transaction
	(1)	(2)	(3)
A. Public disclosure			
Public disclosure (t_{+1})	18.034	-0.162***	-0.550***
	(25.691)	(0.037)	(0.176)
Observations	1,000	1,000	1,000
B. Public disclosure by timing			
Public disclosure (t_{-1})	62.958*	0.043*	0.108
	(33.694)	(0.022)	(0.220)
Public disclosure (t_0)	65.561***	0.013	0.215
	(21.865)	(0.039)	(0.291)
Public disclosure (t_{+1})	-5.009	-0.135***	-0.446**
	(24.751)	(0.041)	(0.169)
Public disclosure (t_{+2})	0.335	-0.073	-0.607
	(18.888)	(0.052)	(0.424)
Observations	975	975	975
District fixed effects	Y	Y	Y
Time fixed effects	Y	Y	Y

Notes: This table reports linear regression analysis of the effect of public disclosure of travel logs of people with COVID-19. The dependent variables are: COVID-19 weekly confirmed cases per million population in district in column (1), log(weekly floating population in millions) in column (2), and log(weekly card transaction in billions) in column (3). The independent variables are: public disclosure, defined as the number of weekly travel logs per thousand population in district, public disclosure (t_{-1}), 1-week lead public disclosure (a week before actual public disclosure), public disclosure (t_{+1}), 1-week lagged public disclosure (a week after actual public disclosure), and so on. All specifications include district fixed effects and time fixed effects. The unit of observation is districts between January and October 2020 on a weekly basis. Standard errors are clustered by district.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

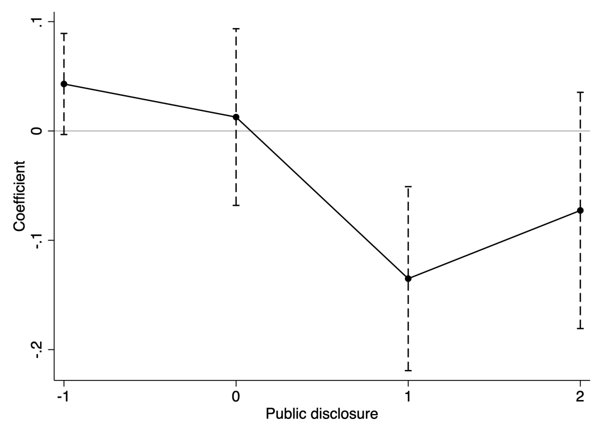
Table 3: THE EFFECT OF PUBLIC DISCLOSURE OF TRAVEL LOGS, CONTROLS

Dependent variable	COVID-19	Floating population	Card transaction
	(1)	(2)	(3)
A. Public disclosure			
Public disclosure (t_{+1})	15.454	-0.163***	-0.572***
	(23.656)	(0.038)	(0.153)
Observations	1,000	1,000	1,000
B. Public disclosure by timing			
Public disclosure (t_{-1})	61.559*	0.045*	0.089
	(35.830)	(0.024)	(0.217)
Public disclosure (t_0)	64.366***	0.014	0.207
	(21.436)	(0.042)	(0.303)
Public disclosure (t_{+1})	-6.106	-0.134***	-0.469***
	(24.307)	(0.042)	(0.164)
Public disclosure (t_{+2})	-0.387	-0.072	-0.639
	(19.712)	(0.048)	(0.400)
Observations	975	975	975
District fixed effects	Y	Y	Y
Time fixed effects	Y	Y	Y
Controls × time trends	Y	Y	Y

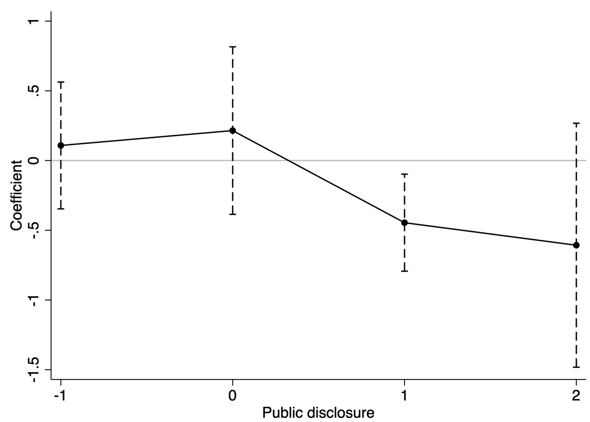
Notes: This table reports linear regression analysis of the effect of public disclosure of travel logs of people with COVID-19. The control variables are: population in thousands, daytime population in thousands, and Gross Regional Domestic Product (GRDP) per capita in million won in the year 2015 interacted with linear time trends. The dependent variables are: COVID-19 weekly confirmed cases per million population in district in column (1), log(weekly floating population in millions) in column (2), and log(weekly card transaction in billions) in column (3). The independent variables are: public disclosure, defined as the number of weekly travel logs per thousand population in district, public disclosure (t_{-1}), 1-week lead public disclosure (a week before actual public disclosure), public disclosure (t_{+1}), 1-week lagged public disclosure (a week after actual public disclosure), and so on. All specifications include district fixed effects and time fixed effects. The unit of observation is districts between January and October 2020 on a weekly basis. Standard errors are clustered by district.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.



(a) COVID-19



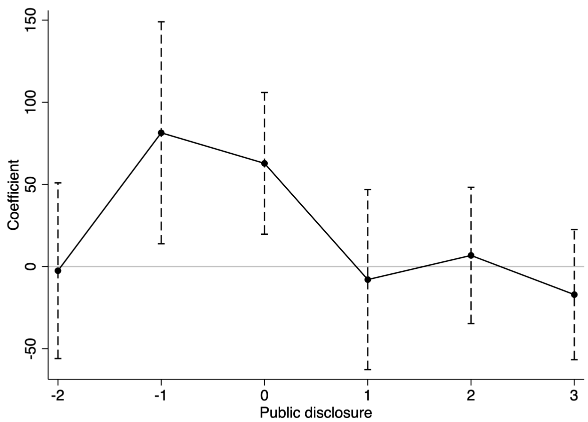
(b) Floating population



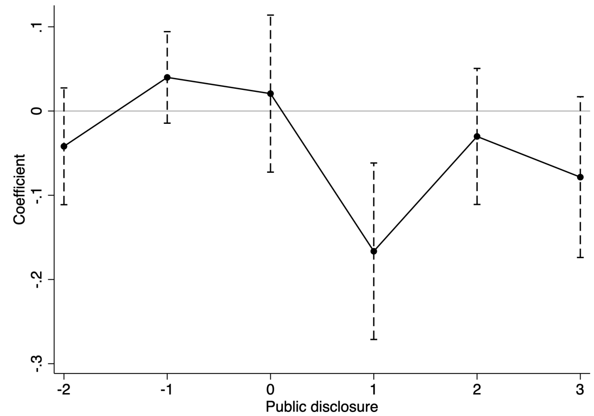
(c) Card transaction

Figure 7: DIFFERENCE-IN-DIFFERENCES

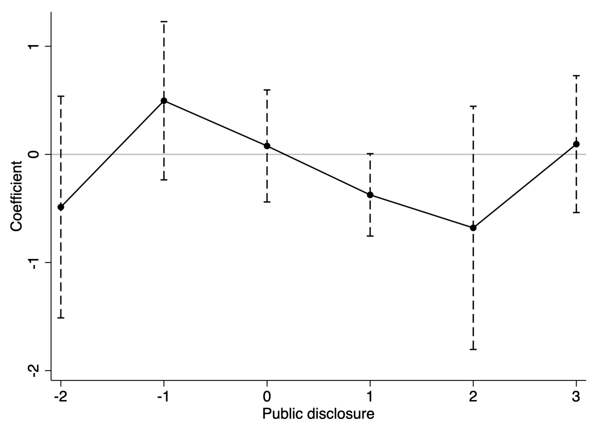
Notes: The figure shows regression coefficients and 95% confidence intervals shown in panel B of the main regression table.



(a) COVID-19



(b) Floating population



(c) Card transaction

Figure 8: DIFFERENCE-IN-DIFFERENCES, EXTENDED PERIOD

Notes: The figure shows regression coefficients and 95% confidence intervals. The period between a week before public disclosure and two weeks after public disclosure in panel B of the main regression table is extended to the period between two weeks before and three weeks after.

4.2 Heterogeneous effect by gender and age

I investigate mechanisms through which public disclosure of travel logs affects foot traffic and card transaction by conducting the heterogeneity analysis by gender and age. Due to COVID-19, closures of schools and daycare centers have increased child care needs, thus decreasing the employment of working mothers (Alon et al., 2020). I hypothesize that, if females are more likely to avoid the risk of infection because of child care needs or the employment drop, then the impact of public disclosure on foot traffic and card transaction would be greater among females.

I find that females were more likely to decrease foot traffic and card transaction. Panel A of Table 4 and Table 5 shows that females decreased floating population by 17.1 percent and card transaction by 62.1 percent, while males decreased them by 15.3 percent and 44.9 percent, respectively.

Previous studies show that the elderly are more likely to avoid the risk of infection because COVID-19 can cause a severe health risk to the elderly (Argente et al., 2021; Brotherhood et al., 2020). However, Shin et al. (2021) find that the impact on foot traffic was greater for younger adults due to the business closures. I hypothesize that, if older adults are more likely to avoid the risk of COVID-19, then the impact of public disclosure on foot traffic and card transaction would be greater among older adults. However, if the business disclosure due to the COVID-19 lockdown is the leading factor compared to the risk avoidance behavior of older adults, then the impact would be greater among younger adults.

I find that younger adults decreased foot traffic and card transaction rather than older adults. Panel A of Table 6 show that younger adults decreased floating population by 17.8 percent and card transaction by 66.4 percent, but Table 7 shows that older adults decreased them by 15.3 percent and 44.9 percent, respectively.

In sum, the effect of public disclosure on floating population and card transaction was greater among females and younger adults.

Table 4: THE EFFECT OF PUBLIC DISCLOSURE OF TRAVEL LOGS, FEMALES

Dependent variable	COVID-19	Floating population	Card transaction
	(1)	(2)	(3)
A. Public disclosure			
Public disclosure (t_{+1})	6.823	-0.171***	-0.621**
	(14.031)	(0.037)	(0.252)
Observations	1,000	1,000	1,000
B. Public disclosure by timing			
Public disclosure (t_{-1})	33.925*	0.039	-0.156
	(18.335)	(0.023)	(0.258)
Public disclosure (t_0)	20.475*	0.002	0.143
	(11.856)	(0.034)	(0.292)
Public disclosure (t_{+1})	-0.367	-0.134***	-0.403**
	(14.736)	(0.038)	(0.185)
Public disclosure (t_{+2})	-0.363	-0.093	-0.871
	(9.867)	(0.057)	(0.524)
Observations	975	975	975
District fixed effects	Y	Y	Y
Time fixed effects	Y	Y	Y

Notes: This table reports linear regression analysis of the effect of public disclosure of travel logs of people with COVID-19 on females. The dependent variables of females are: COVID-19 weekly confirmed cases per million population in district in column (1), log(weekly floating population in millions) in column (2), and log(weekly card transaction in billions) in column (3). The independent variables are: public disclosure, defined as the number of weekly travel logs, not divided by population public disclosure (t_{-1}), 1-week lead public disclosure (a week before actual public disclosure), public disclosure (t_{+1}), 1-week lagged public disclosure (a week after actual public disclosure), and so on. All specifications include district fixed effects and time fixed effects. The unit of observation is districts between January and October 2020 on a weekly basis. Standard errors are clustered by district.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 5: THE EFFECT OF PUBLIC DISCLOSURE OF TRAVEL LOGS, MALES

Dependent variable	COVID-19	Floating population	Card transaction
	(1)	(2)	(3)
A. Public disclosure			
Public disclosure (t_{+1})	11.211	-0.153***	-0.449***
	(13.677)	(0.039)	(0.127)
Observations	1,000	1,000	1,000
B. Public disclosure by timing			
Public disclosure (t_{-1})	29.033	0.047*	0.314
	(18.385)	(0.023)	(0.218)
Public disclosure (t_0)	45.086***	0.024	0.271
	(14.772)	(0.045)	(0.313)
Public disclosure (t_{+1})	-4.642	-0.138***	-0.446***
	(13.483)	(0.044)	(0.159)
Public disclosure (t_{+2})	0.698	-0.052	-0.380
	(12.399)	(0.049)	(0.360)
Observations	975	975	975
District fixed effects	Y	Y	Y
Time fixed effects	Y	Y	Y

Notes: This table reports linear regression analysis of the effect of public disclosure of travel logs of people with COVID-19 on males. The dependent variables of males are: COVID-19 weekly confirmed cases per million population in district in column (1), log(weekly floating population in millions) in column (2), and log(weekly card transaction in billions) in column (3). The independent variables are: public disclosure, defined as the number of weekly travel logs, not divided by population public disclosure (t_{-1}), 1-week lead public disclosure (a week before actual public disclosure), public disclosure (t_{+1}), 1-week lagged public disclosure (a week after actual public disclosure), and so on. All specifications include district fixed effects and time fixed effects. The unit of observation is districts between January and October 2020 on a weekly basis. Standard errors are clustered by district.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 6: THE EFFECT OF PUBLIC DISCLOSURE OF TRAVEL LOGS, YOUNG

Dependent variable	COVID-19	Floating population	Card transaction
	(1)	(2)	(3)
A. Public disclosure			
Public disclosure (t_{+1})	-0.596	-0.178***	-0.664**
	(10.075)	(0.045)	(0.267)
Observations	1,000	1,000	1,000
B. Public disclosure by timing			
Public disclosure (t_{-1})	33.536**	0.061*	0.016
	(13.095)	(0.033)	(0.301)
Public disclosure (t_0)	23.368	0.006	-0.224
	(20.911)	(0.041)	(0.170)
Public disclosure (t_{+1})	-7.549	-0.134***	-0.397**
	(6.989)	(0.043)	(0.163)
Public disclosure (t_{+2})	-4.256	-0.114	-0.630
	(7.389)	(0.068)	(0.442)
Observations	975	975	975
District fixed effects	Y	Y	Y
Time fixed effects	Y	Y	Y

Notes: This table reports linear regression analysis of the effect of public disclosure of travel logs of people with COVID-19 on young people aged below 40. The dependent variables of young people are: COVID-19 weekly confirmed cases per million population in district in column (1), log(weekly floating population in millions) in column (2), and log(weekly card transaction in billions) in column (3). The independent variables are: public disclosure, defined as the number of weekly travel logs, not divided by population public disclosure (t_{-1}), 1-week lead public disclosure (a week before actual public disclosure), public disclosure (t_{+1}), 1-week lagged public disclosure (a week after actual public disclosure), and so on. All specifications include district fixed effects and time fixed effects. The unit of observation is districts between January and October 2020 on a weekly basis. Standard errors are clustered by district.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 7: THE EFFECT OF PUBLIC DISCLOSURE OF TRAVEL LOGS, OLD

Dependent variable	COVID-19	Floating population	Card transaction
	(1)	(2)	(3)
A. Public disclosure			
Public disclosure (t_{+1})	18.630	-0.152***	-0.440**
	(23.085)	(0.034)	(0.200)
Observations	1,000	1,000	1,000
B. Public disclosure by timing			
Public disclosure (t_{-1})	29.422	0.029	0.304
	(23.702)	(0.018)	(0.265)
Public disclosure (t_0)	42.193*	0.018	0.389
	(23.900)	(0.039)	(0.402)
Public disclosure (t_{+1})	2.539	-0.138***	-0.411**
	(19.576)	(0.041)	(0.194)
Public disclosure (t_{+2})	4.590	-0.041	-0.493
	(17.068)	(0.042)	(0.371)
Observations	975	975	975
District fixed effects	Y	Y	Y
Time fixed effects	Y	Y	Y

Notes: This table reports linear regression analysis of the effect of public disclosure of travel logs of people with COVID-19 on old people aged above 40. The dependent variables of old people are: COVID-19 weekly confirmed cases per million population in district in column (1), log(weekly floating population in millions) in column (2), and log(weekly card transaction in billions) in column (3). The independent variables are: public disclosure, defined as the number of weekly travel logs, not divided by population public disclosure (t_{-1}), 1-week lead public disclosure (a week before actual public disclosure), public disclosure (t_{+1}), 1-week lagged public disclosure (a week after actual public disclosure), and so on. All specifications include district fixed effects and time fixed effects. The unit of observation is districts between January and October 2020 on a weekly basis. Standard errors are clustered by district.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

5 Conclusion

I investigate the effect of public disclosure of travel logs of people who tested positive for COVID-19. I measure the effect on the transmission of COVID-19 and economic costs using new confirmed cases, foot traffic and consumption spending. I find that public disclosure did not increase new confirmed cases and decreased foot traffic and card transaction. The economic losses were temporary. The reductions in foot traffic and card transaction did not persist two weeks after public disclosure. Furthermore, I find that the impact of public disclosure was greater among females and younger adults. The results suggest that business closures due to COVID-19 led to the reductions in foot traffic and card transaction.

It should be noted that I use data between January and October 2020 in the early stage of the COVID-19 pandemic in Seoul. As the COVID-19 pandemic has prolonged, business closures in response to COVID-19 and risk avoidance behavior of individuals could have changed. Moreover, the policy on public disclosure has changed over time. Seoul is a capital city in South Korea and one of the busiest and most crowded cities which is the perfect environment for the transmission of infection.

Finally, the results of the study suggest that public disclosure of location information of people with COVID-19 was effective to prevent the spread of COVID-19 in the early stages of the COVID-19 pandemic. Public disclosure caused economic losses for a short term rather than for a long term.

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