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Geographic Restrictions for COVID-19 Stimulus Spending and Public Health Outcomes: Evidence from Big Data in Seoul, South Korea

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Geographic Restrictions for COVID-19 Stimulus Spending and Public Health Outcomes: Evidence from Big Data in Seoul, South Korea

Abstract

During the COVID-19 pandemic, the stimulus payments program has proven to be an effective means of boosting economic activity. Despite the plausible link between these programs and public health outcomes, however, there has been little research on this subject. Our study examines whether the unique policy design restricting geographic locations for COVID-19 stimulus spending could mitigate the spread of the virus. We utilize weekly mobile phone-based mobility data, credit card transaction data, and official COVID-19 cases at a detailed geographic level in Seoul, South Korea. Event-study and difference-in-differences models examined the effects of stimulus payment programs on human mobility and consumer spending patterns. Using the coefficients derived from the model estimating the relationship between COVID-19 infections and commuting inflows, we conduct counterfactual simulations to investigate the role of a geographic restriction in mitigating the potential side effects on public health. The event-study results confirmed a significant increase in people's mobility in Seoul after the disbursement of stimulus payments as stimulus benefits started to translate into increased economic activities. Yet, an additional difference-in-differences analysis based on the card transaction data indicates that a significant share of stimulus transactions was made in the recipients' own neighbourhood. Our simulation testing the differences between policy scenarios with and without geographic restrictions in possible COVID-19 cases indicates that geographic restrictions reduce possible COVID-19 cases by 6.5% compared to the counterfactual scenario (without geographic restrictions). Our findings highlight the importance of geographic restrictions as a policy component in addressing the potential side effects of the stimulus program.

Main

The COVID-19 pandemic has brought significant challenges to not only public health but also economic systems. As tens of thousands of new cases were reported around the world every day, people avoided unnecessary travel and stayed home either voluntarily or under mandatory lockdowns, which severely constrained economic activities both from the demand and supply side. Under the circumstances, several governments announced fiscal stimulus packages to reduce the severity of the economic downturn (Extended Data Table 1). But these efforts may result in unintended consequences: while the stimulus programs were designed to help struggling households and businesses, they could also accelerate the spread of the COVID-19 virus due to an increase in social interactions. On the other hand, vulnerability to COVID-19 may lead consumers to be passive in their economic activities even after the disbursement of stimulus payments. The evidence from the 2020 U.S. CARES Act suggests that the effect of the stimulus payment on restoring consumer confidence and recovering economic conditions was less significant due to health concerns.[1-3] Policymakers in many countries will face challenging dilemmas as both public health and economic recovery are urgent policy agendas when fighting against future pandemics similar to the current one. Therefore, if there is any policy element that can resolve such dilemmas, we need to identify it.

Given the strong evidence of the important role of human mobility in spreading COVID-19 from the public health literature,[4-10] we are able to conjecture that the spatial patterns of stimulus spending are critical in understanding how stimulus payments impact public health outcomes. One potential policy element that can affect these patterns is the geographic restriction for stimulus spending adopted by the South Korean government in 2020. Providing up to $815 of emergency

stimulus payments to all households regardless of their income, the South Korean stimulus program features a careful policy design that restricts consumption category, geographic location, and methods of payment to concentrate its support for hard-hit businesses and mitigate its potential side effects (refer to Supplementary Discussion 1 for the detailed policy design of the Korean stimulus program). Among these, we focus on the geographic restriction, which is directly related to the potential mitigation of contagion caused by stimulus spending. While the original intention was to support local businesses, the restriction discourages unnecessary long-distance trips that could have been promoted by the stimulus program as it does not allow recipients to use stimulus payments beyond the jurisdiction where they reside. Since there had not been a national lockdown or other curfews in South Korea, this geographic restriction might provide a strong policy signal and effectively promote precautionary behaviours. On the other hand, recipients are still required to make physical trips within a limited period of usage (16 weeks) because spending on online platforms was not allowed and stimulus payments were disbursed in the form of credit/debit cards, gift certificates, and local government prepaid cards rather than unrestricted cash payments.

Along with the unique policy design of the stimulus program, the other advantage of performing our analyses in the Korean context is the availability of big data in Seoul Special City, South Korea. We utilize big data including the cell phone–based bilateral flows of people between their residence and destination neighbourhoods over the period of January 2019–August 2020, as well as credit card data with the location information of transactions, consumers' residences, and the number of people testing positive for COVID-19 before and after the disbursement of stimulus payment. We construct a dataset that combines these data on a weekly basis at a detailed geographic level, (*dong*, meaning neighbourhood, in Korean), which is the smallest sub-municipal administrative division in Seoul that contains about 23,500 people, on average (see Extended Data Fig. 1 for data sources). Using this data, we are able to explore where people spend stimulus payments and how far they travel for this spending. We also build the simple SIR (Susceptible-Infected-Recovered) model to estimate the spillover effects of mobility added by stimulus spending on the change in virus infection rates. Counterfactual simulations allow us to accurately isolate the effect of the geographic restriction on public health outcomes.

Despite the plausible link between the stimulus payment policies and public health outcomes during the COVID-19 pandemic, there has been little research on this subject. The majority of economics and finance papers studying the effects of stimulus payments focused on consumer behaviour and welfare outcomes.[11-14] In the public health domain, the main policy discussions were on the efficacy of standard mitigation measures such as safe distancing and lockdowns in preventing infections.[15-19] This is unfortunate because the disbursement of stimulus payments significantly increased public mobility, especially if the program is universal to all citizens, which has been the case in many developed countries including South Korea, Germany, Japan, and Singapore. Our research addresses important policy design questions for this large-scale stimulus program. Although our study uses a single case study of the COVID-19 fiscal stimulus in South Korea, our findings provide broader implications for other contexts where similar stimulus programs are proposed during outbreak of infectious diseases. Also, because the stimulus program is usually offered on a temporary basis, the increases in public mobility and physical contact, accompanied by retail activities, are intensified in a relatively short period of time. We contribute to the public health literature by adding evidence on the relative magnitude of the specific effect of retail consumption–oriented mobility on the virus spread and by suggesting geographic restrictions of retail spending as an alternative mitigation measure to total lockdowns.

Results

We begin our analysis by exploring temporal trends of public mobility before and after the disbursement of stimulus payments. Using general population inflows from the cell phone–based mobility data, we estimate the average inflow changes in each week of 2020 compared with the same week of 2019 after controlling for the week and neighbourhood fixed effects as well as the neighbourhood's COVID-19 infection rates. Figure 1 (Panel A) suggests that a significant increase in cross-neighbourhood mobility within Seoul began from Week 18 (May 4–10, 2020), when the government announced its plan to disburse stimulus payments starting the following week. From Week 18 to Week 31, the coefficients for the interaction terms 'year 2020 × week *i*' ranges from 0.02 to 0.08, meaning that for the period after the disbursement of stimulus payments, the public mobility increased 2%–8%p compared to Week 19 in 2020. Figure 1 shows that cross-city mobility has increased by 2%–12%p in Week 20, one week after the stimulus payment was disbursed, compared to Week 19 (Panel B). Table 1 also shows consistent results that mobility inflows increased across neighbourhoods within Seoul and between cities in South Korea after the disbursement of stimulus payments. These results suggest that the disbursement of stimulus payments is positively related to population mobility within and across cities, although the magnitude of these increases is not very substantial.

To analyse whether such an increase in population mobility is related with the virus's spread, we observe the weekly trends of COVID-19 infection rates in Seoul. Table 1 shows that infection rates were much higher after stimulus disbursement compared with the pre-disbursement period. Figure 1 (Panel C) reports that the increase in infection rates was significant until Week 23 but decreased afterward, suggesting somewhat controlled patterns of the virus's spread. Hence, the big temporal difference shown in Table 1 mainly comes from very low infection rates in the initial period after the COVID-19 outbreak rather than the increase in mobility associated with stimulus spending. It should be noted that there were no substantial changes in public health policy in South Korea during the period.

With some evidence of the slight increase in public mobility after the disbursement of stimulus payments but a less clear link between this increase and the virus's spread, we move to the direct investigation of stimulus spending. Extended Data Fig. 2 shows the majority of transactions with stimulus payments were concentrated in the early usage period. To be specific, 69% and 92% of total stimulus transactions were made in the first 4 and 8 weeks, respectively. This suggests that recipients respond actively to the limited usage period of stimulus payments, which is 16 weeks. Interestingly, Table 1 shows that the number of total transactions increased only slightly after stimulus payment disbursement. As stimulus transactions account for 0.5 out of 9 transactions, regular tractions decreased slightly. This suggests that stimulus payments added only a small number of retail activities. Extended Data Fig. 3 further demonstrates that transactions with stimulus payments accounted for the large proportion of credit card spending. This is particularly true right after the disbursement of stimulus payments.

Where did recipients use their stimulus payments within this short period of time? Figure 2 shows the share of card transactions within the neighbourhood (*dong*) of one's own residence and those in bordering neighbourhoods out of total transactions. What is striking is that consumers made most of these transactions within their own neighbourhood or bordering ones although they could spend elsewhere in Seoul. Overall, around 53% of the transactions are made in one's own neighbourhood and 20% of transactions are made in bordering neighbourhoods. This tendency of choosing their own or bordering neighbourhoods is a lot stronger for consumption with stimulus payments compared with other consumption. These results suggest that the majority of consumers tend to voluntarily choose shorter-distance destinations for the purpose of spending stimulus payments potentially because associated geographic restrictions cautioned against contagion and encouraged precautionary actions.

As a more formal analysis, we perform the difference-in-difference (DID) regression that analyses the geographic locations of credit card transactions before and after the disbursement of stimulus payments, controlling for the difference between 2019 and 2020. For this analysis, we focus on the industries that stimulus payments intend to support, including local grocery markets and restaurants. Results in Table 2 suggest that consumption within own neighbourhood has significantly increased after the disbursement (*Post 20th week*) of stimulus payments in 2020, compared to the weekly consumption patterns found in 2019. In terms of the geographic locations of consumption, people consumed less in bordering and other neighbourhoods in Seoul as well as non-Seoul areas compared to their own neighbourhood after the disbursement of stimulus payments in 2020, compared to the previous year. Consistent with the above descriptive results on direct consumption with stimulus payments, we confirm that the disbursement of stimulus payments did not increase consumption in long-distance destinations. This should have an implication for the virus's spread associated with consumer mobility.

Next, we analyse how stimulus spending has brought spillover effects on the spread of the virus at the district level (*gu* in Korean), the most granular level for which the COVID-19 case data is available. The results in Table 3 consistently show that consumer inflows driven by stimulus payment usage are positively correlated with infection rates, although the magnitude of this effect is smaller compared with those of the neighbourhood's own infection rate prior to 2 weeks and other population inflows. The regular mobility pattern has the strongest effect on the virus inflow into a given neighbourhood (beta: 0.496), followed by the effects of the neighbourhood's own infection rate 2 weeks ago (beta: 0.108) and of stimulus spending (beta: 0.082). These results suggest that the disbursement of stimulus payments targeting offline consumption and aiming to stimulate the local economy has increased related consumer mobility in addition to regular population mobility, and in turn, the risk of COVID-19 infections even when there was a geographic restriction for the usage of stimulus payments.

Finally, we perform the counterfactual simulations for two policy scenarios, with and without geographic restrictions. Figure 3 depicts the weekly average infection rate of the districts in Seoul for these scenarios. First, it suggests that the disbursement of stimulus payments would increase virus infection rates in both scenarios, but not dramatically. One of the potential reasons for this gradual increase in contagion should be related with the only slight increase in public mobility (Figure 1, Panel A & B) accompanied by the substitution effect between stimulus spending and other retail activities (Extended Data Fig. 3). The peaks of the infection rate were commonly found in Week 23, which is four weeks after stimulus payments started being disbursed. We believe that with the highest number of transactions with stimulus payments in the first four weeks (Weeks 20 to 23), virus infection may have been cumulative to the infection rate in Week 23. After Week 23, the infection rate would decrease as the number of transactions with stimulus payments diminishes. These results are consistent with the actual infection rate trend in Seoul (see Figure 1).

More importantly, Figure 3 suggests that the counterfactual scenario without geographic restrictions showed a higher infection rate compared to the scenario with restrictions. In particular, there would have been a higher spread of infection from Week 21 to the end of the usage period if there were no regional restrictions for the usage of stimulus payments even though the gap gets smaller as time goes by. In the 23rd week, which had the largest gap between the two scenarios, the weekly confirmed cases of the 'with restrictions' scenario were 17.2% lower than that of 'without restrictions.' Comparing the two scenarios for the whole period of the usage, the cumulative newly confirmed cases of the 'with restrictions' scenario were 6.5% lower than the 'without restrictions' scenario. From these results, we can conclude that policies imposing geographic restrictions for the usage of stimulus payments contributed to mitigating the spread of the virus, despite the overall increase in mobility and virus infection driven by offline stimulus spending.

Discussion

Our study demonstrates that the policy design could significantly impact public health outcomes and offer insight into how two conflicting policy agendas—stimulating an economy hit by the shock of infectious diseases and mobility restrictions preventing further negative public health outcomes—could be potentially reconciled. We started with the bad news. Public mobility after the stimulus payment disbursement was higher than before, which means more risk for public health. This is not consistent with existing evidence from the U.S., where people increased their stay at home by 3%–5% after the disbursement of EIP (Economic Impact Payment).[20] This increase in population mobility for the case of South Korea is directly related to its policy design for stimulus payments, including the fixed period of usage, money credited in the credit or debit card as the form of disbursement, and the restriction of online usage. Specifically, households experienced a temporary increase in income that they should use within three months, which created an income effect that induced them to consume more than usual. Also, since Korea's stimulus payments were not distributed in cash, people could not use them for other essential uses such as rent or loan repayment. Moreover, because the use of stimulus money was only allowed in offline stores, consumers had to leave their homes and travel. Our results suggest that a similar policy of stimulus payments can bring different results depending on the policy design.

Nevertheless, the majority of stimulus spending was done closer to home when compared to normal consumption. It is notable that the stimulus payments could be spent anywhere in Seoul, so the revealed pattern that recipients are much more likely to spend stimulus payments in their own and bordering neighbourhoods provides an important insight into consumer behaviour. Presumably, the government might have influenced people's behaviour by giving signals with the policy design that imposed geographic restrictions on its usage.

Our results also confirmed that mobility added by stimulus spending has a positive spillover effect on local virus infection rates. Although the magnitude of the effect of stimulus spending–oriented mobility on virus infection was smaller than the effect driven by regular public mobility, the effect is not trivial. Stimulus payments mainly boosted retail consumption in situations where people had significantly reduced such consumption due to health concerns. Hence, our finding suggests that the mobility and physical contact accompanied by increased retail consumption are important drivers of the virus's spread, in addition to general commuting and interactions in workplaces. This is coherent with many initial mitigation initiatives that restricted dining out and other retail activities.

While it is obvious that public mobility increased after stimulus payments were disbursed and increased mobility is directly related to the risk of infection, we found that South Korea has controlled the virus's spread relatively well. Regarding this, we tried to verify the effectiveness of imposing geographical restrictions on the use of stimulus payments through simulations for the case of no geographic restrictions. The simulation results without the geographic restrictions showed a higher level of infection rates. Based on the simulation results, we claim that geographic restrictions played an important role in preventing the rapid spread of the virus across districts and cities.

There are several limitations in this study. While the South Korean government has never implemented lockdown measures during the COVID-19 pandemic, it did impose different levels of social distancing measures starting in March 2020. For example, for one month from March 22, the operation of religious places, entertainment businesses such as clubs, and some indoor sports facilities was restricted fully or partially. Fortunately, there have not been very strict preventive measures in place after the stimulus payment disbursement on May 13 and we included week fixed effects for all our analyses to capture any change in these measures. While we tried our best to make stimulus spending an exogenous shock to mobility, however, public precautionary sentiment or behaviours may have changed over time and this may have influenced their responses to the

geographic restriction for stimulus spending. Also, due to data limitations, we focus only on Seoul Special City, which features a very large urban population and high density. The role of the geographic restriction element for the stimulus program may be totally different for small and low-density areas.

Methods

Data Sources

To analyse the relationships among human mobility, household consumption, and the spread of COVID-19, we construct a dataset that combines both proprietary and public data from multiple sources. First, we use mobile phone–based mobility data provided by SK Telecom, the largest telecommunications company in South Korea. SK Telecom accounts for 42% of the market share with 27 million users, and the data we obtained was weighted for age, sex, and region to represent the mobility patterns of the total population. As mobile phones consistently transmit latitude-longitude coordinates ("pings"), the company has been able to track its consumers as they move with their devices from one location to another. For confidentiality reasons, the SK Telecom data we obtain is anonymized and aggregated at the neighbourhood (*dong*) level, and thus it provides bilateral mobility flows of users between their residence district (*gu*) and destination neighbourhood. The residence is identified by using various criteria including the neighbourhood in which a user's mobile phone is routinely found during the night. The destination neighbourhood is recorded when a user visits and spends more than 30 minutes in the area. The 30-minute threshold was applied to exclude movements by car and/or public transportation. To be consistent with other data used in this paper, the daily SK Telecom data was converted to weekly data, covering the time period of January through August in both 2019 and 2020 (i.e., weeks 0 to 31 in each year). The data structure enables us to observe the changes in mobility patterns before and after the disbursement of the stimulus payments in May 2020 (i.e. week 20), compared to the changes before and after the corresponding week in 2019.

Second, we use weekly credit card transaction data from BC Card, which has the biggest market share in South Korea (23%), for the period from January to August in both 2019 and 2020. South Korea's high debit/credit card adoption rate (around 90%) and the high share of households receiving stimulus payments through their debit/credit cards (75.2%) make the credit card transaction data more valuable to examine the impact of stimulus payments. Similar to the SK Telecom data, the BC Card data is also anonymized and aggregated into highly granular segments of customers and retail stores. As shown in Table 1, customer attributes remained fairly consistent over time. The data contains the number and amount of credit card transactions for the detailed categories of both consumers (i.e., age, sex, income group, occupation type, and residence neighbourhood [*dong*]) and stores (i.e., industry code, whether franchise or not, and destination neighbourhood [*dong*]). Another advantage of the BC Card data is that for each matrix of these categories, it specifies the number and amount of transactions that were paid through the stimulus program. Therefore, we could directly observe the use of stimulus payments, unlike other studies that could only observe overall credit card spending patterns.[20-22] For all analyses, we exclude the transactions that are likely to be non-physical consumption or where the consumer and merchant are not in the same location at the time of the transaction, such as transactions for e-commerce, public transport including taxies, voucher purchases, utility bills, and tax payments.

Finally, we analyse the effects of stimulus spending on COVID-19 cases by using the official COVID-19 cases publicly disclosed by the Korea Disease Control and Prevention Agency (KDCA), the Seoul Metropolitan Government, and each district office. During the COVID-19 pandemic, the South Korean government disclosed location information of the residences and visiting places of people with positive test results to promote precautionary behaviour and curb the spread of

COVID-19 infection. The number of daily confirmed cases was disclosed publicly at the district (gu) level in Seoul and the city- or province-level in non-Seoul areas, which was converted to weekly cases.

Effects of Stimulus Spending on Mobility and Consumption

First, we use the event-study models to examine public mobility trends before and after the disbursement of stimulus payments with the following specification:

$$\ln(inflow_{it}) = \beta_0 + \beta_1 year2020_t + \boldsymbol{\gamma W_t} + \boldsymbol{\delta}(year2020_t \times \boldsymbol{W_t}) + COVIDcases_{i,t-1} + neighbourhood_i + week_t + \varepsilon_{it}$$

where $inflow_{it}$ is the total commuting inflows from all areas to destination neighbourhood i in week t, the variable $year2020_t$ gets a value of one for the year 2020 and zero otherwise, $\boldsymbol{W_t}$ is a vector of weeks from week 5 to week 31 (based on data availability), $COVIDcases_{i,t-1}$ is the number of COVID-19 cases in neighbourhood i disclosed in week $t-1$, $neighbourhood_d$ and $week_t$ are neighbourhood- and weekly fixed effects, respectively. The stimulus payments were distributed in week 20 of 2020, so if the stimulus payments influenced human mobility, we should be able to observe substantial changes in commuting inflows before and after week 20 of 2020, compared to the changes in mobility patterns during the same weeks in 2019.

Similarly, we estimate the difference-in-differences (DID) model to examine the effects of stimulus payments on consumer spending patterns, focusing on its impacts on geographic locations of credit card transactions, with the following specification:

$$\begin{aligned}\ln(transaction_{ijkt}) = {} & \beta_0 + \beta_1 year2020_t + \beta_2 postweek20_t + \boldsymbol{\beta_3 OD_{jk}} \\ & + \beta_4(year2020_t \times postweek20_t) + \boldsymbol{\beta_5}(year2020_t \times \boldsymbol{OD_{jk}}) \\ & + \boldsymbol{\beta_6}(postweek20_t \times \boldsymbol{OD_{jk}}) + \boldsymbol{\beta_7}(year2020_t \times postweek20_t \times \boldsymbol{OD_{jk}}) + \boldsymbol{\psi X_i} \\ & + orig_j + dest_k + week_t + \varepsilon_{ijkt}\end{aligned}$$

where $transaction_{ijkt}$ is the number of card transactions spent in destination neighbourhood k by consumer group i residing in origin neighbourhood j in week t; the variable $year2020_t$ gets a value of one for the year 2020 and zero otherwise as before, $postweek20_t$ indicates whether it is after week 20 either in 2019 or in 2020, $\boldsymbol{OD_{jk}}$ is a vector of origin-destination types such as own neighbourhood, bordering neighbourhood, and other; $\boldsymbol{X_i}$ is consumer group characteristics such as age, sex, income group, occupation type; and origin neighbourhood, destination neighbourhood, and weekly fixed-effects are included in the model. For this analysis, we use the subsample of transactions from week 16 to week 23 as a smaller and more homogeneous time window in the dynamic COVID-19 context. Because almost 70% of stimulus payments were spent within the first 4 weeks, our analysis is not partial. Standard errors are clustered at the neighbourhood level.

Spillover Effects of Mobility Associated with Stimulus Spending on COVID-19 Infection

There have been concerns raised about the stimulus program that it may result in unnecessary travel and social contact, which increase the risk of COVID-19 infection. To quantify the relationship between stimulus payment–induced flows and COVID-19 infection, we run a regression model of the COVID-19 infection rate on the number of visitors who are potentially COVID-19 positive. In doing so, we adopt the SIR (Susceptible-Infected-Recovered) model, which is commonly used in the literature on infectious diseases.[23] Our specific focus is on how people in

Seoul make the transition from the susceptible (S) to the infected (I) state. Hence, we estimate the coefficients of commuting inflows of potentially infected people from the origin district *i* into destination district *j* to use stimulus payments. An assumption is that the pattern of human mobility across the districts within Seoul determines the heterogeneity of infected people's inflows. For example, if all people choose to spend stimulus payments within their own neighbourhoods, neither these in-flows nor virus infection would increase. The rate of infected residents of destination district *j* in week *t* is specified as follows:

$$\ln\left(infection_{j,t}+1\right) = \beta_0 + \beta_1 infection_{j,t-2} + \beta_2 \sum_i (\mathbf{SWM_{ij}} \times infection_{i,t-1}) + \beta_3 \sum_i (\mathbf{SP_{ij,t-1}} \times infection_{i,t-1}) + \varepsilon_{it}$$

where $infection_{j,t}$ is the newly confirmed COVID-19 cases per 100,000 residents of destination district *j* in week *t* after stimulus payments were distributed. We transformed the number of cases with ln (x+1) transformation, which is often used for transforming data that are right-skewed but also include zero values. We include $infection_{i,t-2}$, the destination district *j*'s infection rate two weeks ago, to control for the effects of within-neighbourhood infection. The spatial weight matrix, $\boldsymbol{SWM_{ij}}$, shows travel patterns between origin and destination districts, which is computed as an average weekly number of trips from origin district *i* to destination district *j* during the 8 weeks (i.e., weeks 10 to 17) before the stimulus payments were distributed to capture normal mobility patterns when there was no stimulus payment and to prevent reverse causality. The number of potentially infected visitors to destination district *j* is calculated by aggregating the products of the spatial weight matrix $\boldsymbol{SWM_{ij}}$ and $infection_{i,t-1}$, which is the number of COVID-19 cases per 100,000 residents in origin district *i* in week *t-1*. Similarly, we include the number of potentially infected people from origin district *i* to destination district *j* to spend stimulus payments by multiplying the infection rate in origin district *i* in week *t-1*, $infection_{i,t-1}$, and the number of stimulus transactions between origin district *i* and destination district *j* in week *t-1*, $\boldsymbol{SP_{ij,t-1}}$.

Counterfactual Simulation

Using the coefficients derived from the results of the above spillover effects model, we perform simple simulations predicting weekly infection rates in Seoul for two possible policy scenarios. The first scenario is with a geographic restriction for stimulus spending, which South Korean policymakers have adopted, while the second is a counterfactual without a geographic restriction. For example, some people living in non-Seoul areas may come to a district in Seoul to spend stimulus payments more than in the pre-disbursement period, and in turn, increase the virus's spread. On the other hand, some residents in Seoul may go to other provinces or cities more frequently to use their stimulus payments after disbursement.

For this latter counterfactual scenario, we estimate the number of transactions with stimulus payments that would have occurred if there were no geographic restriction based on several assumptions. First, we assume that the geographic patterns of stimulus spending would be the same as those of the regular card spending for the period after the COVID-19 outbreak but before disbursement of stimulus payments. The second assumption is that the usage period of stimulus payments and the distribution of transactions with stimulus payments across weeks would be the same in both scenarios (Extended Data Fig. 2). Finally, the proportion of transactions with stimulus payments out of total card transactions made by Seoul residents will be the same for non-Seoul

residents. From this assumption, we can use the proportional formula to obtain the number of stimulus payments made by non-Seoul residents in Seoul (see Extended Data Table 2 for details).

The number of stimulus transactions in destination district *j* in Seoul by people living in origin district *i* in week *t* if consumers had no geographical restriction for spending stimulus payments, which is simply expressed as SP^*_{ijt}, is estimated as described in Supplementary Discussion 2. For the first policy scenario with geographic restrictions, we use the actual number of SP transactions. For the counterfactual scenario, we prepare input variables of the prior infection rate regression model with each week's updated infection rate $infection_{j,t}$ for destination district *j* in week *t* recursively to conduct simulations. For every estimation process, we exponentiate predicted $\ln(infection_{j,t+1})$ and subtract 1 to transform it back into the variable of our interest, $infection_{j,t}$, the total infections in each district in each week. Then, we calculate the average infection rate by population weights and compare the trend of these rates for two scenarios.

Statistics & Reproducibility

No statistical method was used to predetermine the sample size for the mobility data; the sample size for consumption behaviour data was based on the availability of the transaction data from BC card. Similarly, the sample size for mobility data was based on the availability of the data from SK Telecom. Data preparation was carried out using Python and ArcGIS Online. Regressions were performed with the STATA statistical package (version 14.0).

Data Availability

First, the mobility dataset is proprietary to SK Telecom and the dataset is subject to strict privacy regulations. Next, the credit card consumption dataset is proprietary to BC Card and subject to privacy regulations. Both datasets were anonymized and aggregated before being shared with the authors. Other datasets including the official COVID-19 cases are publicly accessible.

Code Availability

The custom code that supports the findings of this study is available from the corresponding author upon request.

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Ethics Statement

Conflict of Interests

All authors declare no competing interests.

Consent

We do not use any personally identifiable data, so informed consent is not needed.

Tables

Table 1. Descriptive Statistics in Seoul Special City, South Korea

	Weekly Average Before Stimulus Payment Disbursement (before 20th week)		Weekly Average After Stimulus Payment Disbursement (after 20th week)	
Variables	Mean	Std.	Mean	Std.
COVID-19 Infection rate	(Week 5-19)		(Week 20-35)	
Infection rate per 100K population in district (*gu*)	0.47	0.72	0.75	0.95
No. of district (*gu*)*weeks (Week 5–35)		375		400
Mobility inflows to Seoul neighbourhoods (dong)	(Week 5-19)		(Week 20-31)	
From other districts in South Korea	366,912	210,794	382,142	221,498
From other districts in Seoul	314,518	151,397	327,128	158,449
No. of neighbourhood (*dong*)*weeks (Week 5–31)		6,360		5,512
Credit Card Transactions (average per group)	(Week 5-19)		(Week 20-35)	
No. of total transactions	9.36	14.51	9.50	14.73
No. of stimulus transactions	0.00	0.00	0.48	2.37
No. of transactions except stimulus payments	9.36	14.51	9.02	14.18
Credit Card Customer Attributes (average for all)	(Week 5-19)		(Week 20-35)	
% female users	47.71%	49.95%	48.51%	49.98%
% under 29 years old	21.58%	41.14%	21.11%	40.81%
30 to 39 years old	23.56%	42.44%	23.03%	42.10%
40 to 49 years old	21.53%	41.10%	21.52%	41.09%
50 to 59 years old	17.62%	38.10%	18.03%	38.45%
over 60 years old	15.71%	36.39%	16.31%	36.95%
% with annual income of USD 7,584–15,175	5.91%	23.57%	4.97%	21.74%
USD 15,175–22,763	28.86%	45.31%	28.64%	45.21%
USD 22,763–30,351	41.16%	49.21%	41.55%	49.28%
USD 30,351–37,939	16.90%	37.48%	17.07%	37.62%
USD 37,939–45,527	5.97%	23.69%	6.25%	24.21%
USD 45,527–75,878	1.10%	10.44%	1.36%	11.58%
Over USD 75,878	0.10%	3.21%	0.16%	4.01%
% with occupation with salary	59.56%	49.08%	59.85%	49.02%
self-employed occupation	4.04%	19.69%	4.17%	19.98%
others (no job, students, etc.)	36.40%	48.11%	35.99%	48.00%
No. of credit card observations with a unique group		13,789,564		15,213,294

Stimulus payment was first disbursed on May 13, which falls in the 20th week of 2020. SKT mobility data are available only until Week 31. Our credit card data accounts for customers residing in Seoul. To protect the confidentiality of customer information, our credit card data offers weekly transaction information for a unique group of customers with the same attributes and the same neighbourhood of residence as well as the same neighbourhood and business category of consumption. The Korean government aimed to support offline businesses such as brick-and-mortar businesses. For all our analyses, therefore, we excluded the transactions that are likely to be non-physical consumption or have different locations for the merchant store and actual consumption, such as transactions for e-commerce, public transport including taxies, voucher purchases, utility bills, and tax payment.

Table 2. Difference-in-Difference Model Results for Spatial Patterns of Consumption

ln(number of transactions)	Coef.	S.E.	p-value
Year 2020	–0.006	(0.001)	0.000
Year 2020 × Post 20th week	0.015	(0.001)	0.000
O-D Types (Ref: Dest. = Own Neighbourhood)			
Bordering Neighbourhoods	–0.068	(0.002)	0.000
Other Neighbourhoods in Seoul	–0.060	(0.002)	0.000
Non-Seoul	0.113	(0.011)	0.000
Year 2020			
× Bordering Neighbourhoods	–0.001	(0.001)	0.088
× Other Neighbourhoods in Seoul	–0.003	(0.001)	0.002
× Non-Seoul	–0.008	(0.002)	0.000
Post 20th week			
× Bordering Neighbourhoods	0.002	(0.001)	0.000
× Other Neighbourhoods in Seoul	0.007	(0.001)	0.000
× Non-Seoul	0.008	(0.001)	0.000
Year 2020 × Post 20th week			
× Bordering Neighbourhoods	–0.003	(0.001)	0.000
× Other Neighbourhoods in Seoul	–0.003	(0.001)	0.005
× Non-Seoul	–0.007	(0.002)	0.000
Consumer Characteristics		Yes	
Retail Business Characteristics		Yes	
Orig Fixed-Effects		Yes	
Dest Fixed-Effects		Yes	
Weekly Fixed-Effects		Yes	
Adj. R-squared		0.2914	
Number of Obs.		7,867,672	

For this analysis, we use the subsample of credit card transactions from week 16 to week 23 as a smaller and more homogeneous time window in the dynamic COVID-19 context. Because almost 70% of stimulus payments were spent within the first 4 weeks, our analysis is not partial. The Korean government aimed to support offline businesses such as brick-and-mortar businesses. Reflecting this point, we excluded online and public transport transactions to solely evaluate the effect of stimulus payments.

Table 3. Spill-over Effects of Stimulus Payment on COVID-19 Infection

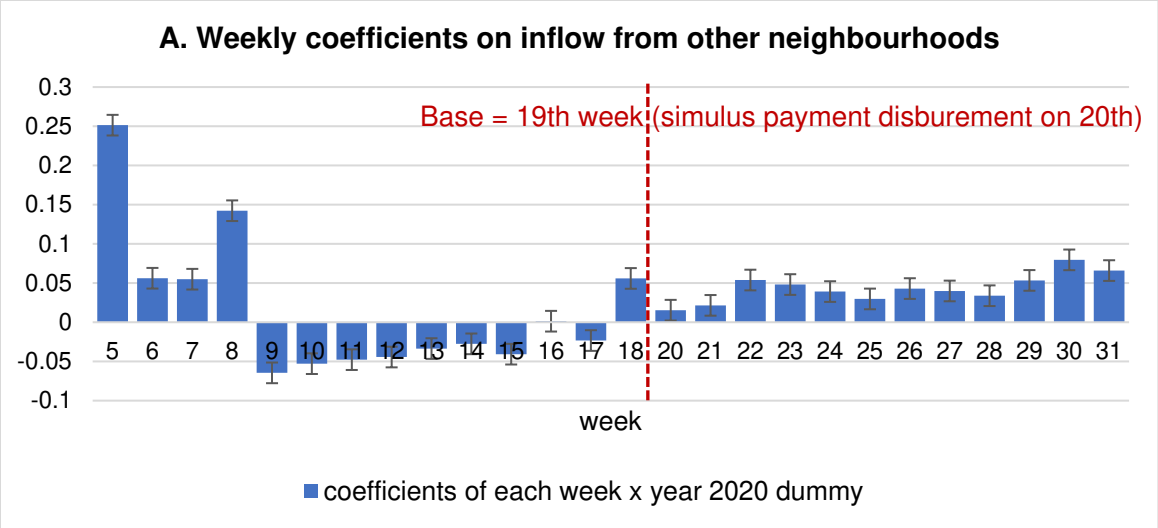
Dependent variable: ln(Infection rate of neighbourhood per 100K population + 1)			
	Coef. (S. E.)	Standardized Beta.	p-value
Neighbourhood's own infection rate 2 weeks ago	0.033 (0.015)	0.108	0.026
Sum of (SWM × infection rate of origin 1 week ago)	0.008 (0.001)	0.496	0.000
Sum of (SP × Infection rate of origin 1 week ago)	0.170 (0.086)	0.082	0.049
Adj R-squared	0.313		
Number of Obs.	400		

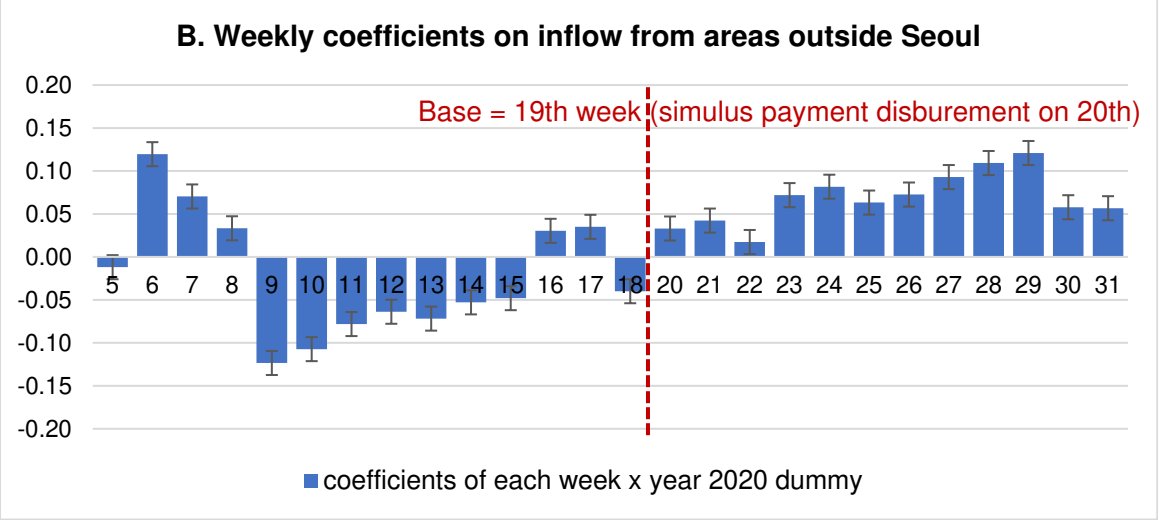
Standard errors are in parentheses.

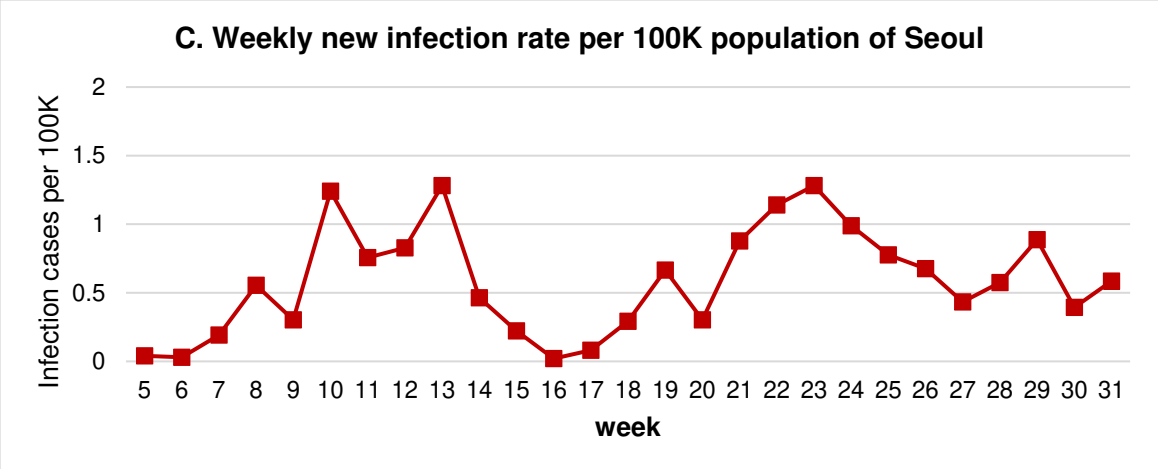
South Korea consists of one special city of Seoul, one special self-governing city of Sejong, six metropolitan cities, and nine provinces. For the area other than Seoul, we consider these 16 divisions as the geographic unit of analysis.

Figures

Figure 1. The Effect of Stimulus Payments on Public Mobility

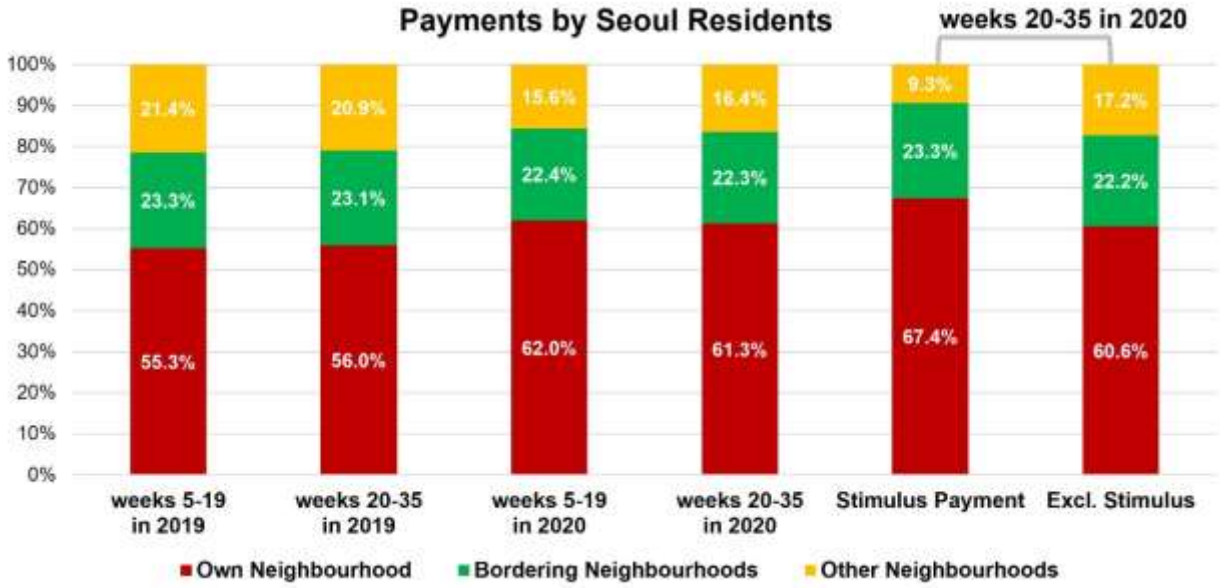






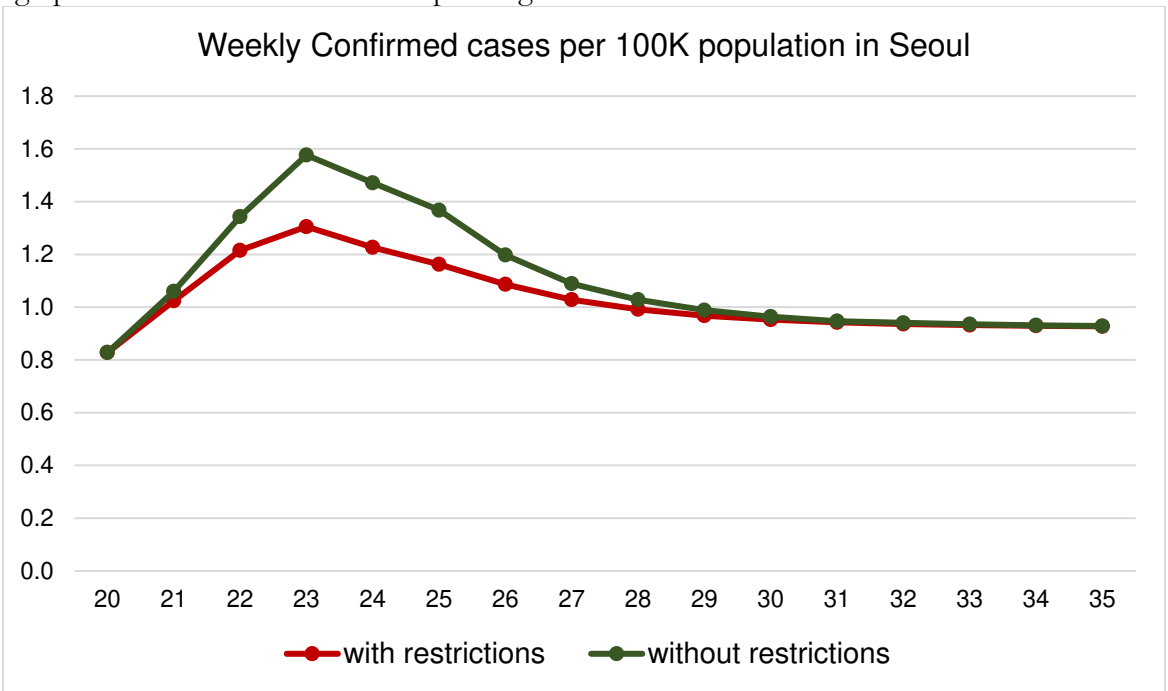
Inflow includes mobility from all other neighbourhoods in South Korea to each neighbourhood in Seoul. In the context of South Korea, the two days in the 18th week were Children's Day and Mother's Day, peak times for family trips and parent visits. However, the impact of anniversaries on public mobility would be absorbed to week fixed effect.

Figure 2. Share of Transaction Locations by Year, Before/After the Disbursement, and Type of Payment (for transactions made by Seoul residents)



Same as Table 1, we only account for customers residing in Seoul and exclude the transactions that are likely to be non-physical consumption or have different locations for the merchant store and actual consumption. Here, bordering neighbourhoods are those that are physically adjacent to the neighbourhood of one's own residence within Seoul. Other neighbourhoods include those that are not bordering neighbourhoods both within and outside Seoul.

Figure 3. Simulation Results for COVID-19 Infection Rates for Policy Scenarios with vs. without Geographic Restriction for Stimulus Spending in Seoul



References

1 Baker SR, Farrokhnia RA, Meyer S, Pagel M, Yannelis C. Income, liquidity, and the consumption response to the 2020 economic stimulus payments. National Bureau of Economic Research; 2020.

2 Chetty R, Friedman JN, Hendren N, Stepner M. The economic impacts of COVID-19: Evidence from a new public database built using private sector data. national Bureau of economic research; 2020.

3 Guerrieri V, Lorenzoni G, Straub L, Werning I. Macroeconomic implications of COVID-19: Can negative supply shocks cause demand shortages? American Economic Review. 2022;112(5):1437-74.

4 Angmo S. Catastrophic Pandemics: Disruption in Tourism Mobility. Virus Outbreaks and Tourism Mobility: Emerald Publishing Limited; 2021. p. 15-30.

5 Anzai A, Nishiura H. "Go To Travel" campaign and travel-associated coronavirus disease 2019 cases: A descriptive analysis, July–August 2020. Journal of clinical medicine. 2021;10(3):398.

6 Chudik A, Pesaran MH, Rebucci A. Voluntary and Mandatory Social Distancing: Evidence on COVID-19 Exposure Rates from Chinese Provinces and Selected Countries–Globalization Institute Working Paper No. 382–Dallas Fed. 2020.

7 Farboodi M, Jarosch G, Shimer R. Internal and external effects of social distancing in a pandemic. Journal of Economic Theory. 2021;196:105293.

8 Fowler JH, Hill SJ, Levin R, Obradovich N. Stay-at-home orders associate with subsequent decreases in COVID-19 cases and fatalities in the United States. PLoS One. 2021;16(6):e0248849.

9 Iacus SM, Santamaria C, Sermi F, Spyratos S, Tarchi D, Vespe M. Human mobility and COVID-19 initial dynamics. Nonlinear Dynamics. 2020;101(3):1901-19.

10 Kapoor R, Rho HA, Sangha K, Sharma B, Shenoy A, Xu G. God is in the rain: The impact of rainfall-induced early social distancing on covid-19 outbreaks. Covid Economics. 2020;24:76-110.

11. Kim S, Koh K, Lyou W. Do COVID-19 stimulus payments stimulate the economy? Evidence from card transaction data in South Korea. Evidence from Card Transaction Data in South Korea (September 29, 2020). 2020.

12 Kubota S, Onishi K, Toyama Y. Consumption responses to COVID-19 payments: Evidence from a natural experiment and bank account data. Journal of Economic Behavior & Organization. 2021;188:1-17.

13 Misra K, Singh V, Zhang Q. Frontiers: Impact of Stay-at-Home-Orders and Cost-of-Living on Stimulus Response: Evidence from the CARES Act. Marketing Science. 2022;41(2):211-29.

14 Feldman N, Heffetz O. A grant to every citizen: Survey evidence of the impact of a direct government payment in Israel. National Tax Journal. 2022;75(2):229-63.

15. Allcott H, Boxell L, Conway J, Gentzkow M, Thaler M, Yang D. Polarization and public health: Partisan differences in social distancing during the coronavirus pandemic. Journal of public economics. 2020;191:104254.

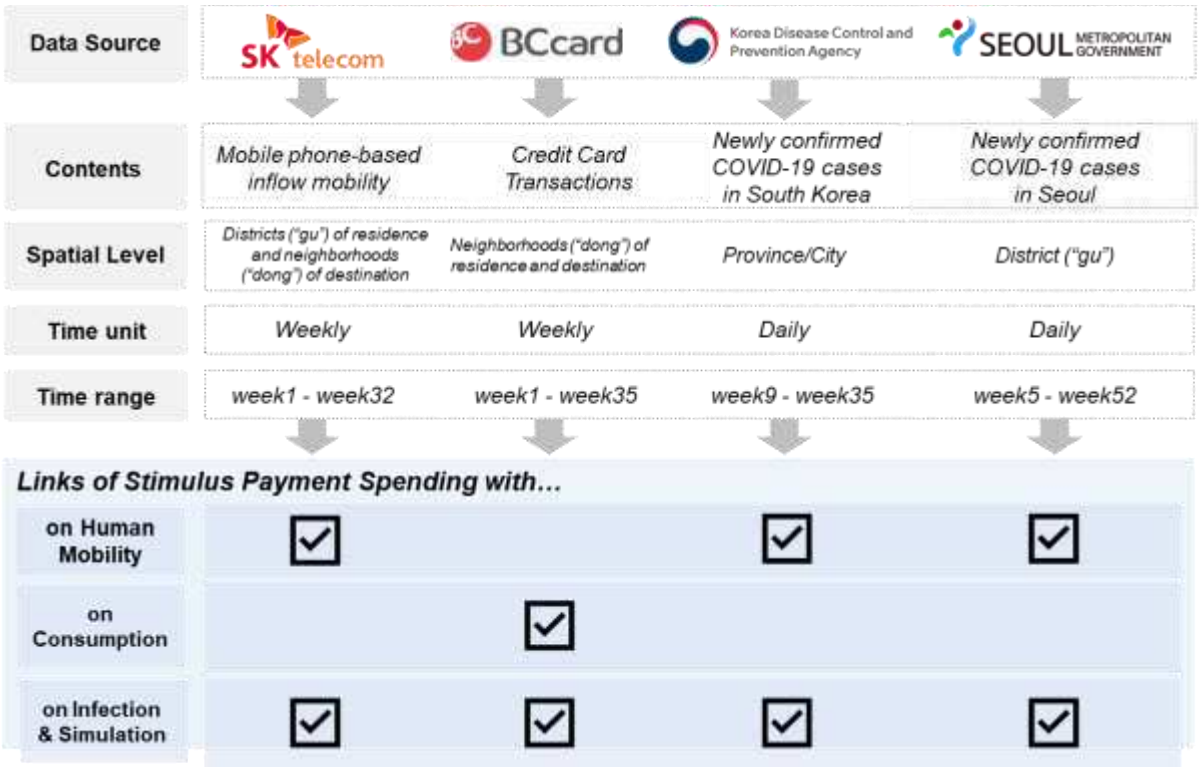
16. Gollwitzer A, Martel C, Brady WJ, Pärnamets P, Freedman IG, Knowles ED, et al. Partisan differences in physical distancing are linked to health outcomes during the COVID-19 pandemic. Nature human behaviour. 2020;4(11):1186-97.

17. Dave D, Friedson AI, Matsuzawa K, Sabia JJ. WHEN DO SHELTER-IN-PLACE ORDERS FIGHT COVID-19 BEST? POLICY HETEROGENEITY ACROSS STATES AND ADOPTION TIME. Economic Inquiry. 2021;59(1):29-52.

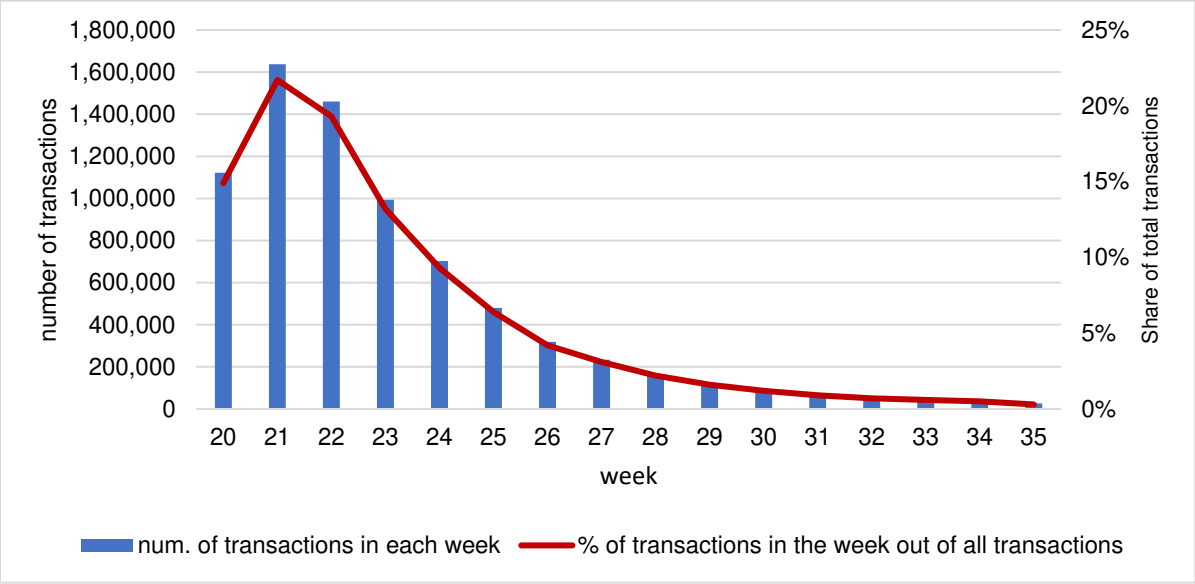
18 Gupta S, Nguyen T, Raman S, Lee B, Lozano-Rojas F, Bento A, et al. Tracking public and private responses to the COVID-19 epidemic: evidence from state and local government actions. American Journal of Health Economics. 2021;7(4):361-404.

19 Wright AL, Sonin K, Driscoll J, Wilson J. Poverty and economic dislocation reduce compliance with COVID-19 shelter-in-place protocols. Journal of Economic Behavior & Organization. 2020;180:544-54.
20 Zhang R. Economic impact payment, human mobility and COVID-19 mitigation in the USA. Empirical Economics. 2022;62(6):3041-
21 Kim MJ, Lee S. Can stimulus checks boost an economy under COVID-19? Evidence from South Korea. International Economic Journal. 2021;35(1):1-12.
22 Lee KO, Lee H. Public responses to COVID-19 case disclosure and their spatial implications. Journal of Regional Science. 2022;62(3):732-56.
23 Argente D, Hsieh CT, Lee M. The cost of privacy: welfare effects of the disclosure of Covid-19 cases. The Review of Economics and Statistics. 2022 Jan 6;104(1):176-86.

Extended Data Fig. 1. Summary of Data and Sources

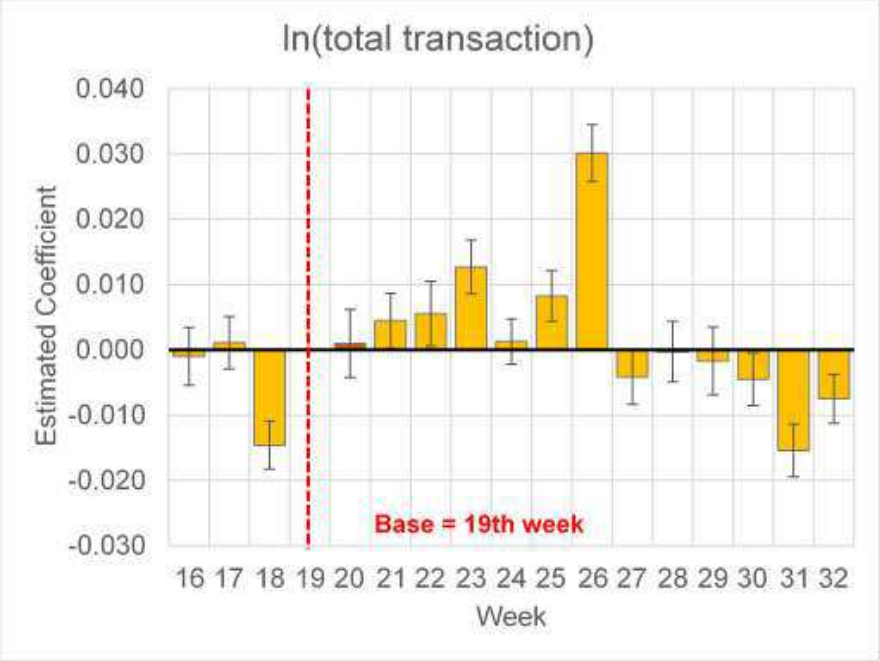


Extended Data Fig. 2. Temporal Trend of Stimulus Transactions by Seoul residents

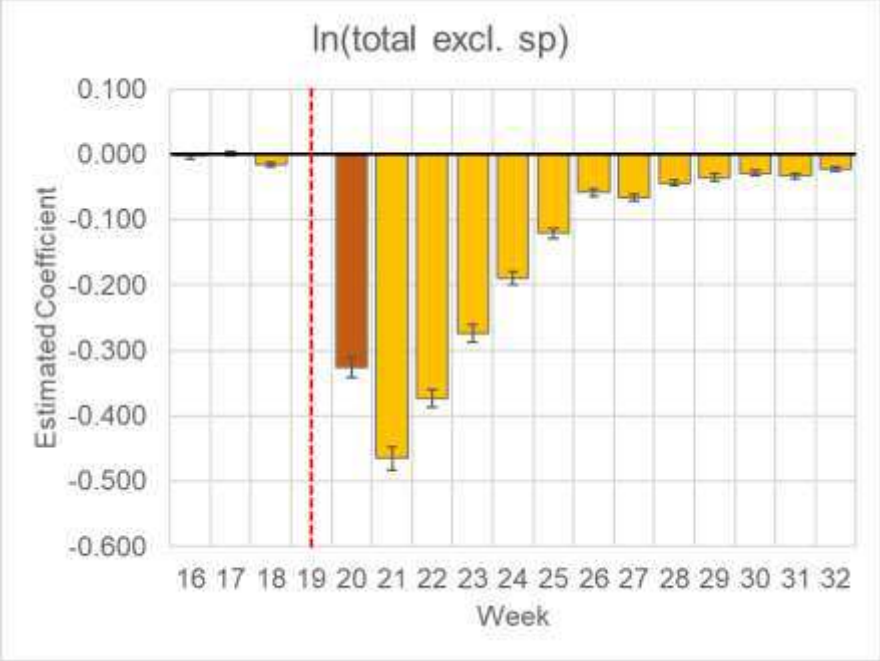


Extended Data Fig. 3. The Effect of Stimulus Payments on Other Spending

A: Event study results for the number of all transactions



B: Event study results for the number of transactions excluding those with stimulut payments



Same as Table 1, we only account for customers residing in Seoul and exclude the transactions that are likely to be non-physical consumption or have different locations for the merchant store and actual consumption. We use the aggregate number of transactions rather than the number transactions per customer because of our data constraints.

Extended Data Table 1. Policy Design Comparisons of Stimulus Payment across the Countries

Policy Question	Policy Design	Examples
Eligibility	Universal payment for all households	- South Korea's Stimulus Payment - Singapore's Solidarity Payment - Israel's Grant to Every Citizen - Japan's Special Cash Payment - Germany's Kinderbonus
	Income for lower-income households (progressive)	- US CARES - UK's Universal Credit
	Support for the affected group (e.g. self-employed)	- Germany's Soforthilfe and Überbrückungshilfe
Form of Payment	Non-cash/One time	- South Korea (credit/debit cards) - Hong Kong's Consumer Voucher Scheme
	Cash/One time	Most other countries
Geographic Restriction for Consumption	Yes	South Korea (within the city of residence)
	No	Most other countries
Restriction on Business Type	Exclusion	South Korea's exclusion of ecommerce, non-SME, and higher-risk businesses
	Target	- Singapore's Discovery Voucher - Japan's Go to Travel

Extended Data Table 2. Estimation of stimulus transactions by non-Seoul residents in Seoul

week	**A = B×C/D** num. of SP made by non-Seoul residents in Seoul	B. num. of non-SP made by non-Seoul residents in Seoul	C. num. of SP made by Seoul residents in the whole country	D. num. of non-SP made by Seoul in the whole country
wk20	538,123	1,834,404	1,122,348	3,825,962
wk21	965,189	2,000,362	1,637,446	3,393,621
wk22	1,082,869	3,259,510	1,459,944	4,394,532
wk23	486,775	1,962,409	993,505	4,005,266
wk24	483,303	3,377,119	702,887	4,911,475
wk25	217,189	2,153,575	479,922	4,758,751
wk26	148,372	2,134,421	318,853	4,586,886
wk27	141,118	3,102,055	234,023	5,144,278
wk28	98,521	3,170,369	164,162	5,282,690
wk29	60,297	2,523,126	122,822	5,139,465
wk30	26,069	1,328,281	87,661	4,466,585
wk31	39,761	3,112,787	68,128	5,333,571
wk32	32,954	3,248,761	53,435	5,267,807
wk33	19,008	2,149,219	44,279	5,006,663
wk34	13,960	1,823,148	35,619	4,651,762
wk35	11,390	1,682,365	25,977	3,836,954

Supplementary Discussion 1. Detailed policy design of the Korean stimulus program

To support households and businesses that experienced economic hardship and stimulate the local economy after the COVID-19 outbreak, the South Korean government provided emergency stimulus payments to all households, up to US$815 (or KRW 1 million, applying the exchange rate of May 20, 2020: US$1 = 1,226.79 KRW) in May 2020. The stimulus payments were provided in the form of universal basic income regardless of household income, and the actual amount was determined by the number of household members.

Compared to the COVID-19 stimulus payment programs implemented in other countries during the period, the one in South Korea had several unique features that might influence intended and unintended outcomes. First, the South Korean government imposed several restrictions on where the stimulus payments could be used. The restriction was placed both on the geographic location of consumption and on industries and business types, addressing concerns that increased mobility and economic activities by the stimulus payments might contribute to the further spread of COVID-19.

From this perspective, recipients could not use the stimulus payments beyond the jurisdiction where they reside. The boundary of jurisdictions is shown below. For example, recipients who live in Seoul could not use the payments in other cities and/or provinces, and vice versa. This feature made the stimulus payments function as local currency and thus stimulate the local economy. The geographic restriction was also designed to discourage any unnecessary long-distance trips that could have been promoted by the stimulus program. This feature is in stark contrast to the Japanese government's "Go To Travel" campaign during the period, which aimed to boost the domestic tourism industry amid serious concerns over its unintended consequences (Anzai and Nishiura, 2021).



As another safeguard against the spread of COVID-19, the stimulus payments could not be used at "high-risk" businesses including karaoke bars, clubs, salons, spas, and casinos. At the same time, the South Korean government aimed to support the businesses hit hard by the pandemic, such as local mom-and-pop and brick-and-mortar businesses, so large retail stores (e.g., department stores, big-box stores, duty-free shops) and online platforms (e.g., e-commerce business, food delivery services) were excluded from the program as well.

The stimulus payments were provided in the form of credit/debit cards, gift certificates, and local government prepaid cards rather than unrestricted cash payments. Among those options, more than three quarters of households (75.2%) chose to receive their stimulus payments as credit/debit cards (Ministry of the Interior and Safety, 2021). South Korea has one of the world's highest debit/credit card ownership rates. According to the Bank of Korea, the ownership rates of debit cards and credit cards in 2015 were 90.2% and 96.1%, respectively, when they were 76% (debit card) and 67% (credit card) in the United States (Kwon and Kim, 2016).

Finally, the application for the stimulus payments began on May 11, 2020, and the stimulus payments were distributed as early as May 13, 2020. The stimulus payments were designed to expire on August 31, 2020, if not spent, so recipients were encouraged to use the stimulus payments immediately rather than save them for future use.

References

Anzai, A., & Nishiura, H. (2021). "Go To Travel" campaign and travel-associated coronavirus disease 2019 cases: A descriptive analysis, July–August 2020. Journal of clinical medicine, 10(3), 398.

Kwon, N., & Kim, M. (2016). Results of the 2015 Survey of Consumer Payment Choice and Its Implications. *Consumer Payment Choice Survey Report No. 2016-9*. Seoul: Bank of Korea. https://www.bok.or.kr/portal/cmmn/file/fileDown.do?menuNo=200706&atchFileId=KO_00000000000132318&fileSn=1

Ministry of the Interior and Safety. (2021). Completion of Disbursement of the COVID-19 Stimulus Payments [Fact Sheet]. Ministry of the Interior and Safety. https://www.mois.go.kr/cmm/fms/FileDown.do?atchFileId=FILE_00105802UdqqFzh&fileSn=1

Supplementary Discussion 2. Estimating the number of stimulus transactions in counterfactual simulation

In this paper, we explore the role of geographic restrictions in the stimulus payments program by comparing the model estimates of COVID-19 infections under the policy scenarios with and without a geographic restriction. In the model, stimulus payment–induced visitors who are potentially COVID-positive are one of the major determinants, and therefore it is crucial for us to estimate the number of stimulus transactions in one location by a resident from another location under the different scenarios. In this Appendix, we explain how we estimate the number of stimulus transactions in a counterfactual scenario (i.e., stimulus payments without a geographic restriction).

In the no-geographic-restriction scenario, weekly stimulus transactions in Seoul consist of two components: (1) the stimulus transactions spent in Seoul by Seoul residents and (2) the stimulus transactions spent in Seoul by non-Seoul residents:

$$\sum_{i}\sum_{j\in Seoul} SP^{*}_{ijt} = \sum_{i\in Seoul}\sum_{j\in Seoul} SP^{*}_{ijt} + \sum_{i\notin Seoul}\sum_{j\in Seoul} SP^{*}_{ijt}$$

where SP^{*}_{ijt} is the estimated number of stimulus transactions spent in destination area *j* by residents in origin area *i* in week *t*.

First, we estimate the number of stimulus transactions spent in the areas within Seoul by people residing in Seoul under the no-geographic-restriction scenario. Here, we assume that the spatial distribution of stimulus transactions among Seoul residents would be the same as that of overall consumer spending patterns before the stimulus payment program. We use the geographic distribution of overall credit card transactions during the eight weeks before the disbursement of stimulus payments (i.e., weeks 10 to 17), and thus Seoul residents would spend stimulus payments both inside and outside of Seoul as they spent during weeks 10–17:

$$\sum_{i\in Seoul}\sum_{j\in Seoul} SP^{*}_{ijt} = \sum_{i\in Seoul}\sum_{j\in Seoul} SP_{ijt} \times \frac{\sum_{i\in Seoul}\sum_{j\in Seoul} TotalSpending_{ij,10-17}}{\sum_{i\in Seoul}\sum_{j} TotalSpending_{ij,10-17}}$$

where $TotalSpending_{ij,10\text{-}17}$ is the number of credit card transactions spent in destination area *j* by residents in origin area *i* during weeks 10–17, and SP_{ijt} is the number of stimulus payments in destination area *j* by residents in origin area *i* in week *t* as before.

Second, we estimate the number of stimulus transactions in Seoul by non-Seoul residents when there was no geographic restriction. Unfortunately, since our data only provide information on credit card transactions by non-Seoul residents in Seoul, we are not able to use the same method shown above. Instead, we assume that the ratio of stimulus transactions to regular transactions among Seoul residents is the same for non-Seoul residents. Therefore, we estimate the number of stimulus transactions in Seoul by non-Seoul residents by multiplying their regular transactions with this ratio:

$$\sum_{i\notin Seoul}\sum_{j\in Seoul} SP^{*}_{ijt} = \sum_{i\notin Seoul}\sum_{j\in Seoul} RP_{ijt} \times \frac{\sum_{i\in Seoul}\sum_{j\in Seoul} SP_{ijt}}{\sum_{i\in Seoul}\sum_{j\in Seoul} RP_{ijt}}$$

where RP_{ijt} is the number of regular transactions in destination area *j* by residents in origin area *i* in week *t*. SP_{ijt} is the number of stimulus payments in destination area *j* by residents in origin area *i* in week *t*.

Lastly, we distribute the estimated stimulus transactions made in Seoul, both by Seoul residents and by non-Seoul residents obtained through the process mentioned above, across districts (*gu*) so that

we can multiply them by the infection rate in each district. Again, we assume that the spatial distribution of stimulus transactions across districts is the same as the overall consumer spending patterns before disbursement of stimulus payments (i.e., weeks 10–17). Therefore, the number of stimulus transactions spent in destination district *j* by residents in origin district *i* in week *t* is determined by:

$$SP^*_{ijt} = \sum_i \sum_{j \in Seoul} SP^*_{ijt} \times \frac{TotalSpending_{ij,10-17}}{\sum_i \sum_{j \in Seoul} TotalSpending_{ij,10-17}}$$

where $TotalSpending_{ij,10\text{-}17}$ is the number of credit card transactions spent in destination district *j* by residents in origin district *i* in weeks 10–17, and SP^*_{ijt} is the estimated number of stimulus payments in destination district *j* by residents in origin district *i* in week *t* based on the estimation approaches mentioned above.