The effect of adaptive mobility policy to the spread of COVID-19 in urban environment: intervention analysis of Seoul, South Korea

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Abstract:

Although severe mobility restrictions are recognized as the key enabler to contain COVID-19, there has been few scientific studies to validate such approach, especially in urban context. This study analyzes mobility pattern changes in Seoul, South Korea that adopted adaptive approach toward mobility. Intervention analyses reveal that major mobility reduction did occur two weeks before the city’s case peak. Such voluntary adjustments exhibit strong preference shift toward private mode from public transit. Large reductions occurred in non-essential and high-contact activities of shopping and dining, while work and Starbucks trips were less affected. The collective evaluation reveal that major changes in epidemiology, mobility and policy occurred simultaneously, with no lagging nor leading contributors. Our study demonstrates that collective understanding the mutual aspects among mobility, epidemiology and policy is essential. Incremental and flexible mobility restriction is not only possible but necessary, especially for a pandemic of extensive spatial and temporal scales.

1. Introduction

Although mobility restriction has been embraced as the most immediate and effective crisis response policy in epidemics, there has been lack of scientific study to validate such hypothesis. In fact, the vast spatial and temporal scales of COVID-19 have revealed that the effectiveness of mobility restriction is highly dependent on timings and approaches1-5. Globally, two success cases of Taiwan and New Zealand had opted the early border closure6,7, over which the government have a complete control. Once having missed the opportunity to lock down the national borders in the earliest stage, the actual experiences of mobility restriction have been far from seamless and vary greatly across the countries and regions1-5.

In the first 100 days of pandemic, South Korea has observed 10,752 confirmed cases and 244 fatalities, or 207.4 and 4.7 per 1M populations. In Seoul, the toll was 633 confirmed (65.1/1M population) and 2 fatalities (0.2/1M population). Such low numbers are rather counterintuitive, if considering the city is not only one of the most densely populated cities in the world, but also the national and a global hub of mobility and socio-economic activities.

It is also noteworthy that South Korea had never mandated severe mobility restrictions such as lockdown or shelter-in-place8,9. The 14-day quarantine rule was applied only to those with symptoms and possible exposures10,11. Rather, the emphasis had been on the public safety guidelines of washing hands and wearing face mask, while the focus of mobility restriction had
been on avoiding high-contact activities, all under the condition of ‘as much as possible’. The level of mobility restriction had been modified according to the progression of the coronavirus.

Taking advantage of the unique mobility experience South Korea has provided, this study aims to evaluate the evolution of urban mobility over the first 100 days in relation with the policy and epidemiology. The major intervention timings in mobility patterns were detected in the amount of reduction compared to the same period of the previous year. Findings in mobility are then evaluated in collective manner by tracing and relating the intervention timings of mobility and epidemiology, as well as the policy timeline.

2. Mobility

2.1. Data and Method

Relevant data were collected from various public sources. Two trip modes (subway, traffic volume) and four trip purposes (work trip, Starbucks, dining, shopping) are represented in hourly scale. The trip mode data are the direct observations, and the trip purpose data is estimated using cellphone geo-locations in 19,153 geospatial units. The amount of reduction was measured compared to the same day-of-week in the previous year as $1 - \frac{\text{hourly value of 2020}}{\text{hourly value of 2019}}$. For instance, day 19 (Friday Feb 7, 2020) was matched with Friday Feb 8, 2019. The time-of-day analyses were carried out separately whenever relevant.

The intervention days and hours were detected by tracing the major structural changes in a time series. Data $(y)$ is decomposed into $m+1$ segments of constant intercept values $(\beta_0)$ given the linear model $y = \beta_0 + \epsilon$. Intervention timings are the $m$ points which is the last data point before the intercept transitions from one to another. Summary of data (Table S1) and the intervention estimation results (Table S2) are provided in the supplementary materials.

2.2. Results

Fig. 1 shows the results in plots, and estimation details are included in Table S2. In trip mode, the intervention days of largest reductions were detected at 21:00 on day 33 in traffic volume and 08:00 on day 34 in subway. Considering the late hour of transition in traffic volume, it is reasonable to conclude that both modes share the common major intervention day of 34, which is Saturday. However, they differ significantly in magnitude. The public mode of subway shows over 40% reduction, whereas the private mode of traffic volume shows less than 15%. The difference is even greater during the afternoon hours, showing nearly 50% reduction in subway compared to less than 10% in traffic volume. Also, reductions in subway ridership experienced its first shift as early as day 16. Such findings manifest the strong shift in mobility preference to the private mode of choice.

Among the four trip purposes, less essential and high contact trip purposes of dining (Michelin starred and Bib-gourmand restaurants) and shopping (department stores) show the largest reductions of longest durations, whereas the essential activity of workplace shows the least amount of reduction. Trips to the nearly ubiquitous Starbucks turned out to be semi-essential to Seoulites, showing the least amount of reduction during the morning hours. Overall, all mobility categories share the common interventions day of major reduction on day 34, Saturday, except for the essential and semi-essential purposes of work (day 36, Monday) and Starbucks trips (day 37, Tuesday).
3. Epidemiology of COVID-19

3.1. Data and method

Epidemiological data provided by KCDC contains the daily count of the confirmed, fatality and released, as well as the contact tracing information. The progress of the virus was measured in two aspects, including the daily count and the geospatial evolution over two consecutive days. As for the daily new cases, intervention detection was carried out in the same manner as mobility.
Although the daily tolls are the universal measure to monitor epidemiological progress, the complexity and perception cannot be the same when 100 new cases concentrated in a single location compared to dispersed uniformly. From the mobility standpoint, the geospatial evaluation is even more relevant to further understand its spatio-temporal impact. In this paper, we propose to measure the grouped distance and Hausdorff distance to quantify the geospatial dispersion.

Given $P_t = \{p_t: point contact location on day t\}$, the grouped distance is defined as

$$d_g(P_t, P_{t+1}) = \frac{1}{|P_t|} \sum_{p_t \in P_t, p_{t+1} \in P_{t+1}} |p_t - p_{t+1}|,$$

which is the average pairwise distance between day $t$ and $t + 1$. Hausdorff distance is defined as

$$d_H(P_t, P_{t+1}) = \max \left( \max_{p_t \in P_t} \min_{p_{t+1} \in P_{t+1}} |p_t - p_{t+1}|, \max_{p_{t+1} \in P_{t+1}} \min_{p_t \in P_t} |p_t - p_{t+1}| \right).$$

By definition, $d_H > d_g$ means that there exists at least one location that doesn’t intersect with any locations of the other day within the radius of $d_g$. Conversely, $d_g > d_H$ means that all locations of one day intersect with at least one of the locations of the other day within $d_g$. The sustained period of $d_H > d_g$ can be characterized as the escalation/de-escalation phase, where new cases popping up in isolation from the existing mass. Likewise, the sustained period of $d_g > d_H$ can be characterized as the geospatial peak phase, where the cases over two days are located relatively close to each other.

### 3.2. Results

In Fig. 2, the structural changes of the daily count of the nation and the top four regions with over 500 cases are shown. City of Daegu and Gyeongbuk Province account the majority of national cases in the first half of the 100 days, and share similar major upward (day 33 and 35) and downward (day 48 and 50) intervention days. Seoul and Gyeonggi Province show lagged intervention days with much lower number of confirmed cases, especially per 1M population. In Seoul, the first upward shift is detected on day 48, about two weeks later than day 35 of the national peak. Gyeonggi Province, which encapsulates Seoul and borders North Korea, shows the first increase on day 33, followed by another major increase on day 54.

Considering the nationwide peak (35 to 50) coincides with Daegu, our results clearly indicate that the nation’s peak period is mostly due to the regional epidemic concentrated in Daegu-Gyeongbuk Province, and the active nationwide diffusion had occurred in the latter half of 100 days. In other words, South Korea had had about two weeks to observe, learn and prepare for the virus before it reached the most vulnerable areas of highest populations.
Fig. 2. Daily confirmed cases and corresponding structural changes of South Korea (black), Seoul (blue), Gyeonggi Province (cyan), Daegu (red), Gyeongbuk Province (cardinal)

In Fig. 3, the spot values of $d_g$ and $d_H$ are shown with their structural changes. The escalation (~ day 29) and de-escalation (day 80~) phases are identified, and the geospatial peak phase is between day 30 and day 79. Considering the persistent period of the non-zero new cases had begun from day 31, our findings suggest that it is most likely that Seoulites had perceived the coronavirus finally reaching their neighborhood, much earlier than the beginning of the case peak on day 48.

Fig. 3. The grouped distance ($d_g$) and Hausdorff distance ($d_H$) values and the structural changes

4. Collective Assessment of Epidemiology, Mobility and Policy

In this section, the results presented in section 2 and 3 are evaluated in collective manner, by tracing and relating the intervention days of epidemiology and mobility, as well as the major policy timeline (Figure 4). The structural change of the COVID-19 related search terms sourced from NAVER search engine was added to represent direct changes in perception.

In the figure, the period surrounding day 34 (Saturday) stands out with utmost significance. In all categories under evaluation, the major structural changes were detected few days apart from day 34, suggesting no leading or lagging contributors during the most active and uncertain period in the 100 days. Although the National Level 4 Alert was declared on day 35\textsuperscript{10,11}, it is nearly
impossible to imagine that such simultaneous interventions can be designed and realized overnight with a single policy. Moreover, the later implementation of strict social distancing\textsuperscript{10,11} from day 63 seems to have influenced the voluntary adjustment prolonged for the remaining days, rather than adding more pressure to reduce mobility even further.

In fact, our findings strongly support that the early adjustment in mobility is the result of voluntary adjustment, mostly at the personal level. What exactly triggered such proactive adjustments requires a richer set of geodemographic and mobility data, monitored over an extended period of time. Assuming psychology plays a major role, a dramatic increase in the COVID-19-related search term frequencies on day 33 may provide some clues. It is most likely that such increase is strongly related to the fact that the national toll had reached 100 new cases for the first time on day 33. Incorporating the geospatial peak period starting as early as day 30 in Seoul, it might have been not just the simple count of 100, but also the city’s heightened perception of the virus finally reaching their neighborhoods in scale.
Fig. 4. Intervention days of epidemiology, geospatial dispersion, mobility and the major policy implementations
5. Conclusions and Limitations
This study adopted a data-centric approach to evaluate the evolution of the COVID-19 pandemic in Seoul, South Korea over the first 100 days from the aspects of epidemiology, geospatial dispersion, mobility and policy. Unlike some research findings on the role of policy in South Korea\textsuperscript{1,15}, our intervention analyses showed that there had been no leading nor lagging contributors during the 100 days. Adjustment in mobility started long before the strict social distancing implementation, most likely spurred by the voluntary sacrifice of individuals.

The Seoul case demonstrate that the essence of mobility restriction is the collective coordination between the general public and policy, accompanied with additional measures such as safety guidelines. The roles of mobility, epidemiology and policy are intertwined in the larger context, and any declaration of success or criticism on failure of mobility policy seems one dimensional. Our findings also shed some lights on the possibility and necessity of adaptive mobility restriction in future epidemics. Mobility should be viewed and adapted as the integral part of the crisis, rather than a simple and immediate option to call and wait to see what happens. If we need to live with the virus in the present and possibly in the future, it is necessary to adopt a holistic approach toward the multi-faceted nature of pandemic.

Our study has a few limitations to note. Our study does not cover the healthcare aspect of the outbreak. From the earliest days, KCDC’s emphasis have been testing, isolating and tracing potential cases, while supplying unlimited medical attention to those in critical conditions\textsuperscript{10,11,15}. It also has continuously emphasized the importance of face mask when leaving one’s home\textsuperscript{10,11,15}. Such targeted approach for the affected, potentially affected, and unaffected populations combined with the unfathomable sacrifice of medical community is one of the major contributors. Due to data limitations, the results and insights from this study is specific to the first 100 days up to April 28, 2020. How people will react in the following days or to a new pandemic requires continuous research efforts.

Data and materials availability: Data used in this paper are collected from public sources, and can be provided for future research. More details on data sources and accessibility can be found in our data summary paper\textsuperscript{12}.

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**Author contributions:** Yoonjin Yoon conceptualized and led the study, conducted the intervention analysis, interpreted results, designed figures and wrote the paper. Soohwan Oh and Jungwoo Cho collected, processed and cross-checked the subway, POI and NAVER search data, and organized references. Seyun Kim collected and processed the traffic volume data. Yuyol Shin collected contact tracing data and calculated the grouped and Hausdorff distance. Namwoo Kim visualized the POI locations for the figure in the supplementary information. Haechan Cho collected and crosschecked the COVID-19 data. All authors discussed the results and participated in reviewing and editing the manuscript.
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Supplementary Materials:
Notes on data used in the study
Figure S1
Tables S1-S2
References (16-24)
Notes on Data used in the study

COVID-19

Epidemiological data of the first 100 days consists of two datasets: COVID-19 daily tolls and contact tracing information. The main source is the Kaggle COVID-19 open data, which contains both the daily tolls and the longitude-latitude coordinate of the contact tracing information. Once collected, the data were crosschecked with the daily briefings by KCDC and regional authorities, and any incorrect values were modified. Contact tracing information is the itinerary of each confirmed patient from 2 days before symptom onset to the day of quarantine. The itinerary is recorded with the coordinate of stores or buildings visited, transportation modes used for each day. In our paper, the coordinates of places in the itinerary were used in the geospatial analysis. In the nation, Seoul is the only city that traced the contact locations of all patients for the 100 days, resulting in the total of 2,425 contact locations of 638 confirmed cases.

Mobility

The subway ridership and traffic volume of year 2019 and 2020 are direct observation counts. Subway ridership data was collected from Seoul Metro, and consists of the hourly number of passengers getting on and off at 275 stations. Traffic volume data was collected from Seoul TOPIS, and consists of the hourly traffic volumes at 105 locations.

2019 and 2020 data of four trip purposes are based on the estimated current population provided by Korea Telecom (KT), which is the estimates based on the cellphone geolocations from 8,266 base stations. The estimates are available in hourly scale in the geospatial unit of Jipgyegu, which is the smallest statistical unit (SSU) in Seoul. Trip purpose data used in our analysis is the changes in the current population of the Jipgyegu that each Points of Interests (POIs) belongs to. Locations of Starbucks stores (512), Michelin-listed restaurants (80), and the major department stores (17) were directly extracted using Google Places API based platform. The top 5 workplace locations were first identified from the national travel survey of year 2017. The travel survey data is available in 424 Traffic Analysis Zones (TAZ), and contains the number of employees per TAZ. The top 5 TAZs account 13.5% of total employment in the city. Out of 19,153 Jipgyegus in total, 560 were included in our mobility analysis. In Figure S1, the locations of Jipgyegu of each trip purpose categories are shown.

Reductions are measured by matching the day-of-week of 2020 to 2019. For instance, Friday Feb 7, 2020 (day 19) was matched with Friday Feb 8, 2019. Two exceptions are the Lunar New Year and the Independence Day holidays, which were matched with the corresponding holidays of 2019. For more details, please refer to our data summary paper.

NAVER search trend of COVID-19 related search terms

Search trend of the terms related to COVID-19 was collected from NAVER data labs. NAVER is the leading search engine in South Korea, accounting nearly 58% of the nation’s search volume in the last 2 years. NAVER provides the daily search volume data for user-specified keywords in relative value, within the scale of 0 to 100, where 100 being the highest search volume during the designated period.
Figure S1. POI locations in Jipgyegu

Top 5 employment (Workplace)

Starbucks

Department Stores (Shopping)

Michelin-listed Restaurants (Dining)
Table S1. Summary of data description

| Category          | Region        | Period                          | Frequency | Name                        | Description                                                                 | Source                      |
|-------------------|---------------|---------------------------------|-----------|-----------------------------|-----------------------------------------------------------------------------|-----------------------------|
| Epidemiology      | Nationwide    | Jan 20, 2020 – Apr 28, 2020     | Daily     | COVID-19 case               | Number of confirmed and fatality cases; Confirmed date of each patient; District- or city- level residential information of each patient | COVID-19 open data\(^{16}\); KCDC\(^{14}\) |
|                   |               |                                 |           | Contact tracing             | Contact tracing information of confirmed patients in Seoul                  |                             |
| Trip mode         | Seoul         | Jan 20, 2020 – Apr 28, 2020     | Hourly    | Subway ridership           | Hourly subway ridership counts extracted from the credit card usage information | Seoul Metro\(^{17}\)        |
|                   |               |                                 |           | Traffic volume              | Hourly traffic volume at 105 count locations                                | Seoul TOPI\(^{18}\)        |
| Trip purpose      | Seoul         | Jan 20, 2020 – Apr 28, 2020     | Hourly    | Workplaces top 5           |                                                                 | Seoul Open Data Plaza\(^{19}\) |
|                   |               |                                 |           | Starbucks                   |                                                                 |                             |
|                   |               |                                 |           | Department stores          |                                                                 |                             |
|                   |               |                                 |           | Michelin Starred & Bib Gourmands |                                                                 |                             |
| Search trend      | Nationwide    | Jan 20, 2020 – Apr 28, 2020     | Daily     | NAVER search trend         | The relative proportion of search frequency related to ‘COVID-19’ on NAVER search engine | NAVER Data labs\(^{23}\)    |
Table S2. Intervention Analysis Results

| Category               | Intervention Estimates: Day (Hour) | Day-of-Week | 95% Confidence Intervals | Fitted Values   |
|------------------------|------------------------------------|-------------|--------------------------|-----------------|
| **COVID-19**           |                                    |             |                          |                 |
| Nationwide             | 35, 50, 77                         | Sun, Mon, Sun | [33,56], [49,53], [76,80]| 17.2, 452.1, 94.5, 16.5 |
| Seoul                  | 48, 81                             | Sat, Thu    | [42,49], [80,87]        | 2.3, 14.6, 2.3  |
| Gyeonggi Province      | 33, 54, 76                         | Fri, Fri, Sat| [31,34], [50,56], [75,78]| 0.4, 8.1, 17.1, 4.7 |
| Daegu                  | 35, 50                             | Sun, Mon, Sun| [32,36], [49,53]        | 8.9, 350.7, 25.6|
| Gyeongbuk Province     | 33, 48                             | Fri, Sat    | [30,34], [47,51]        | 0.8, 68.1, 6.1  |
| **Trip Mode**          |                                    |             |                          |                 |
| Subway                 | Operating Hours (5-24)              | Tue, Sat, Sun| [16,16], [34,34], [77,88]| 0.0186, 0.1490, 0.4058, 0.3636 |
|                        | Commute (7-9, 18-20)               | Thu, Fri    | [17,21], [32,34]        | 0.0049, 0.0984, 0.3279 |
|                        | Afternoon (14-16)                  | Mon, Fri, Sun, Sun | [15,18], [33,34], [50,64], [81,89]| 0.0304, 0.2096, 0.3647 |
|                        | Nighttime (20-23)                  | Mon, Fri, Sun | [15,18], [33,34], [80,86]| 0.0501, 0.1656, 0.4397, 0.3677 |
| Traffic                | All day                            | Thu, Fri, Mon | [17,24], [33,34], [53,60]| 0.0075, 0.0390, 0.1342, 0.1036 |
|                        | Commute (8-10, 18-20)              | Fri          | [27,35]                   | 0.0102, 0.0781  |
|                        | Afternoon (14-16)                  | Fri, Sun     | [31,35], [52,63]        | 0.0233, 0.0950, 0.0535 |
|                        | Nighttime (20-23)                  | Fri, Sun     | [32,34], [51,61]        | 0.0389, 0.1701, 0.1166 |
| **Trip Purpose**       |                                    |             |                          |                 |
| Workplace              | All day                            | Mon, Fri    | [36,36], [57,81]        | 0.0092, 0.1256, 0.1071 |
| Top 5 (Mon-Fri)        | Commute (8-10, 18-20)              | Mon          | [33,37]                   | 0.0044, 0.1466  |
|                        | Lunch (11-13)                      | Mon          | [32,37]                   | -0.0189, 0.1191 |
| Starbucks              | Opening Hours (7-22)               | Fri, Tue, Sun, Sun | [17,21], [37,37], [53,62], [72,79]| 0.0233, 0.0573, 0.1951, 0.1720, 0.1416 |
|                        | Morning (7-9)                      | Mon          | [35,38]                   | 0.0237, 0.1192  |
|                        | Afternoon (13-16)                  | Fri, Sun     | [32,34], [55,89]        | 0.0310, 0.1906, 0.1523 |
| Department Stores      | Opening Hours (10-21)              | Sat, Sun, Sat, Sun | [33,34], [47,53], [65,70], [84,86]| 0.1103, 0.2981, 0.2487, 0.3050, 0.2167 |
|                        | Afternoon (13-16)                  | Fri, Sun     | [32,34], [82,90]        | 0.1410, 0.3012, 0.2297 |
| Michelin listed        | Dining (11-14, 18-22)              | Sat, Sun, Sun | [33,34], [70,83]        | 0.0872, 0.2756, 0.2370 |
| Restaurants            | Lunch (11-14)                      | Fri          | [32,34]                   | 0.0681, 0.2417  |
|                        | Dinner (18-22)                     | Fri          | [33,34], [80,86]        | 0.1009, 0.2905, 0.2368 |
| Geospatial Dispersion  | $d_H$ Day 18-89                    | Sun, Tue     | [27,30], [74,81]        | 11.5, 6.9, 10.6  |
|                        | $d_g$ Day 18-89                    | Mon, Tue     | [28,34], [36,70]        | 7.4, 11.0, 9.9   |
| NAVER Search Trend     |                                    | Fri, Sat, Sun| [31,34], [27,54], [61,67]| 8.8, 49.4, 25.7, 18.3  |
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