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Dynamic interactions of COVID-19 incidences, mobility, and social distancing policies in seoul: A VAR model approach

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COVID-19 incidence, mobility, and social distancing policies are interdependently linked, with the pathways and level of influence varying over time by region. Using weekly, district-specific time series data, we examined whether the effect and underlying pathways of social distancing policies on changes in COVID-19 incidence and mobility differ between commercial and non-commercial districts in Seoul. We employed the Vector Autoregression with Exogenous variables (VARX) model to analyze the interdependencies among COVID-19 incidences, mobility patterns, and social distancing policies over time from June 2020 to November 2021 across Seoul, including district-specific effects. The model incorporated vaccination coverage as an external variable to account for population-level immunity. Impulse Response Functions (IRFs) were used to interpret the results of the citywide VARX model, illustrating how changes in one variable influenced others over time. Social distancing policies had minimal direct effects on incidence rates but indirectly reduced them by decreasing mobility. Mobility observed two weeks prior demonstrated a positive correlation with current COVID-19 incidence, particularly in commercial districts, indicating that increased movement significantly contributes to transmission. On the other hand, rising COVID-19 cases led to decreased mobility, especially in non-commercial districts, likely driven by fear of infection and heightened self-restriction. Policies were more effective in reducing mobility within commercial districts, likely due to stricter enforcement and higher population density, which amplified compliance impacts. Reduced mobility in commercial districts following stricter policies indicates that targeted restrictions in high-traffic areas can effectively help control COVID-19 transmission in Seoul. In contrast, the more pronounced voluntary movement reductions in non-commercial areas, driven by increased incidence, suggest that enhanced regular testing could play a more significant role in disease control in these regions. While policies reduce mobility, their slower impact on incidence rates, at least a two-week time lag, highlights the need for proactive implementation to achieve measurable decreases in transmission.

COVID-19 incidence, mobility, and social distancing policies are interdependently linked, forming a dynamic feedback loop. Overall, an inverse relationship between social distancing policy and incidence has been consistently observed, although specific measures varied in effectiveness. For example, public event cancellations reduced new infections by about 20%, while school closures yielded 15% decrease[1]. Social distancing policy also generally drove down mobility, with mandatory measures proving more impactful than voluntary ones: a mandatory stay-at-home order produced a 16.7% decrease in mobility compared to 8.4% under non-mandatory guidance[2]. Timing and stringency were also important factors, as evidenced by Wuhan's early, strict lockdown that sharply limited both inflows and outflows[3]. Meanwhile, the association between mobility and incidence was generally inverse yet sometimes non-linear, with certain "superspreader" locations accounting for a disproportionate share of infections[2,4–7]. Reduction in mobility often led to notable decline in case growth within a two- to four-week lag[6]. However, these initial reductions were not always sustained, as mobility often rebounded once restrictions were eased[3,8].

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Most existing studies focus on pairwise relationships—either the impact of policy on incidence or the correlation between mobility and incidence—without fully capturing the ways in which these three factors co-evolve in a feedback loop over time. For example, social distancing policies are known to suppress mobility[6,9–11]which in turn can reduce COVID-19 incidence[12–16]. At the same time, the spread of the virus itself deters movement, as quarantine, isolation, hospitalization, and the fear of infection further limit mobility[17,18]. Moreover, most analyses rely on brief observation periods from early 2020 and overlook how successive COVID-19 waves can alter policymakers' and the public's responsiveness to evolving epidemic conditions. As a result, the varying impacts of the timing, duration, and stringency of social distancing measures, particularly across different population densities and levels of commercial activity, remain underexplored. Similarly, the synergistic or competing effects of policy, voluntary behavioral change, and vaccination on incidence trajectories have received less attention. These gaps underscore the need for more dynamic, region-specific modeling strategies that better capture how mobility, incidence, and social distancing policy intersect.

The objective of our study was to investigate the dynamic relationships among COVID-19 incidence, mobility, and social distancing policies. While a few studies have explored the interdependence of these three factors using the Vector Autoregression (VAR) model[6,19,20]this approach is particularly useful for capturing feedback loops, such as how a rise in cases reduces mobility, which in turn influences policy stringency or adaptation, and vice versa. We adopted a Vector Autoregression with Exogenous variables (VARX) model, incorporating vaccination coverage as an exogenous variable. This allowed us to examine the temporal modeling of feedback processes (bidirectional and indirect relationships among all three factors) with minimal assumptions about causal direction while accounting for the effects of vaccination coverage, rather than isolating each pair independently. Unlike the structural equation model, which often requires predefined causal structures and is better suited for cross-sectional data[21]VARX estimates how variables influence one another over time through lagged effects. This makes it ideal for understanding evolving dynamics under pandemic conditions, such as delayed behavioral responses and time-lagged policy impacts.

Using the VARX model, we examined whether the effect, duration, and underlying pathways of social distancing policies on changes in COVID-19 incidence and mobility differ across districts over time in Seoul, South Korea. Seoul's metropolitan context offered a unique opportunity for this analysis, with its uniform public health policy implementation, comprehensive district-specific mobility datasets, and reliable, frequent reporting of COVID-19 infections and vaccination coverage. By quantifying the direction and duration of interactions among the three factors, this study provides valuable insights into the temporal patterns and causal pathways linking COVID-19 incidence, mobility, and social distancing policies. These findings can inform more effective strategies for disease control in urban settings.

Methods

Data sources

We used four sets of data sources, including (1) district-specific weekly COVID-19 cases from the Korea Disease Control and Prevention Agency[22](2) weekly human mobility data based on mobile phone records from SK Telecom, which is the telecommunications company with the highest number of subscribers in South Korea, (3) social distancing policy data from the Korea Disease Control and Prevention Agency[23]and (4) vaccination coverage data (defined as the number of people who had completed the primary vaccination series in South Korea) from our world data[24].

Seoul metropolitan city consists of 25 autonomous districts ("*gu*" in Korean) and 426 administrative neighborhoods ("*dong*" in Korean). Human mobility data were based on the frequency of movements inside and outside *dong*, which were defined based on whether participants visited other areas outside their resident areas for at least 30 min, which is a threshold adopted by the data provider to capture meaningful trips while excluding short-term pass-throughs. In order to align the mobility with the incidence data, which is only available at *gu* level, we aggregated the weekly frequency mobility data from *dong* to *gu* level.

We also used the weekly frequency for incidence data to avoid a seasonal effect induced by lower reporting during weekends. Throughout the pandemic, the South Korean government adjusted its policy levels, transitioning between 3-, 5-, and 4-level systems[23]. The social distancing policy data included three distinct levels between June 28, 2020, and November 6, 2020, based on daily case counts and transmission patterns; five levels from November 6, 2020, to July 11, 2021, to better address regional disparities in outbreaks and fine-tune restrictions based on risk levels, preventing blanket lockdowns and allowing for more targeted interventions; and four levels from July 12, 2021, to November 1, 2021, to balance virus control with economic activity and reflect the improved ability to manage outbreaks, particularly with a partially vaccinated population[24], .

To create a consistent policy index across time, we standardized each day's policy level by dividing it by the maximum level for that period (e.g., Level 2 out of 3 becomes 0.67). For each week, we then calculated a weighted average of the daily standardized values, using the number of days each level was in effect within the week. This generated a continuous weekly policy stringency index ranging from 0 to 1. Given that Seoul's policies were uniformly implemented citywide, the social distancing policy data were consistent across both city-level and district-level analyses. Although various social distancing policies were implemented starting in March 2020, we focus on the analytic time window from June 28, 2020, to November 1, 2021, when the level-based social distancing policy was in effect, as shown in Fig. 1. This allows us to systematically capture the dynamic relationships among key variables: incidence, mobility, and social distancing policy.

Model overview

In this study, we employed the Vector Autoregression with Exogenous variables (VARX) model, detailed by Hamilton, J. D[25]. to analyze the interdependencies among multiple time series variables, focusing on how COVID-19 incidences, mobility patterns, and social distancing policies influence each other over time in Seoul,

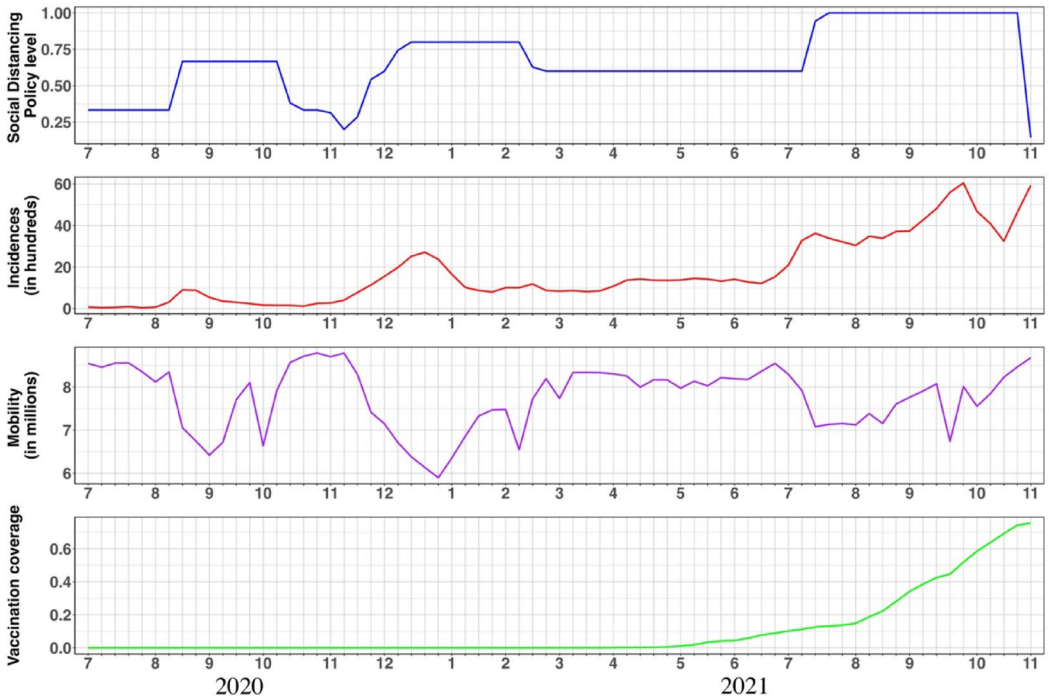


Fig. 1. Weekly time series patterns of social distancing policy, incidence, mobility and vaccination coverage from June 28, 2020 - November 1, 2021 in South Korea.

while accounting for the effect of vaccination coverage as an external factor. The VARX model allows us to capture the dynamic relationships between these variables by considering their mutual influences, as well as the impact of vaccination as an exogenous variable that may affect but is not influenced by the endogenous variables in the system.

To comprehensively explore these relationships, we constructed a total of 26 models—one for the city as a whole and one for each of Seoul's 25 districts. This approach enables us to analyze both the overarching trends across Seoul and the localized variations within individual districts, providing a multi-level understanding of the interactions among incidences, mobility, and social distancing policies.

We estimated the VARX model using the ordinary least squares (OLS) method, which is widely used for such models due to its straightforward implementation and interpretability[25,26]. The estimation process was conducted using the $"VAR"$ function in R package $"vars"$[27].

Lag selection

For lag selection in the citywide model, we considered four key criteria: Akaike Information Criterion (AIC), Hannan-Quinn Criterion (HQ), Schwarz Criterion (SC), and Final Prediction Error (FPE). This was conducted using the $"VARselect"$ function in R package $"VAR"$[27]. The Schwarz Criterion, also known as the Bayesian Information Criterion (BIC), was ultimately selected as it effectively balances model complexity and goodness of fit. Based on this criterion, we chose a 2-week lag, which appropriately accounts for the dynamics between the endogenous variables (COVID-19 incidences, mobility patterns, and social distancing policies) while incorporating the effect of the exogenous variable (vaccination coverage). This decision aligns with practical considerations in pandemic studies, where policy effects often manifest over relatively short periods.

To ensure consistency and comparability, we applied the same 2-week lag structure to each district-level model. This uniform lag choice allows for a coherent comparison across Seoul's districts, providing a standardized framework for examining the localized dynamics of COVID-19 spread, mobility shifts, and social distancing policy impacts while maintaining alignment with the citywide model's design.

Equation

The VAR model used in our analysis is represented by the following equation:

$$Y_{i,t} = A_{i,1}Y_{i,t-1} + A_{i,2}Y_{i,t-2} + B_iX_{i,t} + \epsilon_{i,t}$$

- $Y_{i,t}$ is a vector containing the variables of interest for district i at time t (e.g., COVID-19 incidences, mobility, and social distancing policy)
- $A_{i,1}$ and $A_{i,2}$ are coefficient matrices for district i, capturing the influence of past values of the endogenous variables on their current values.
- $X_{i,t}$ is a vector of exogenous variables (e.g., vaccination coverage) for district i, which influence the endogenous variables but are not influenced by them.

- B_i is the coefficient matrix associated with the exogenous variables $X_{i,t}$ for district i.
- $\epsilon_{i,t}$ represents the error terms for district i, assumed to be white noise.

A unit root test was performed to ensure the stationarity of each time series dataset used in these models, with detailed results provided in the Appendix.Mo.

Impulse response functions (IRFs)

To interpret the results of the citywide VARX model, we utilized Impulse Response Functions (IRFs). IRFs allow us to analyze how a shock to any one variable (e.g., a sudden increase in COVID-19 incidences, changes in mobility, or shifts in social distancing policy) impacts the other variables over time. This approach allows us to examine both the immediate and lagged effects among these variables, providing a comprehensive understanding of their dynamic interrelationships within the system.

The mathematical representation of the IRFs is given as follow:

$$IRF_y\left(k, \Omega_{t-1}, \epsilon_t\right) = E\left[y_{t+k} | \Omega_{t-1}, \epsilon_t\right] - E\left[y_{t+k} | \Omega_{t-1}\right]$$

where:

- y_{t+k} is the response variable at horizon k.
- Ω_{t-1} represents the information set before the shock at time t.
- ϵ_t is the shock applied to the impulse variable at time t.

For each combination of impulse and response variables (social distancing policy, mobility, and incidences), we calculated the IRFs. In the VARX model, we also account for the effect of exogenous variables (e.g., vaccination coverage), although they are not directly impacted by shocks in the endogenous variables. The exogenous variables influence the dynamic response of the system but do not receive feedback from the endogenous variables. This setup allows us to isolate and analyze the effects of social distancing policy, mobility changes, and COVID-19 incidences within the system, with vaccination coverage serving as an external influencing factor.

Model fitting and IRFs calculation

We first fitted a VARX model to the variables of interest (social distancing policy, mobility, and incidence rates) while including vaccination coverage as an exogenous variable. This allowed us to ensure that the model adequately captured the lagged interdependencies among the endogenous variables and accounted for the external influence of vaccination coverage. Next, we generated shocks for each endogenous variable in the system and used the "irf" function in R package "$vars$"[27] to calculate the impact of these shocks on all other variables over the next 10 time periods. To account for uncertainty in the estimates, we enabled bootstrapping ($'boot = TRUE'$), simulating the distribution of IRFs by repeatedly drawing shocks from the residuals and recalculating the IRFs, which provided robust estimates and confidence intervals. Finally, we plotted the IRFs for each pair of impulse and response variables and saved them for further analysis and visualization.

Model visualization

All the maps were generated using R software (version 4.5.0)[28] with the packages " $ggplot2$ "[29] and "sf" [30] for spatial visualization. Seoul administrative boundary shapefiles were obtained from the open-source GitHub repository "southkorea-maps" (South Korea Maps, 2018)[31]. All visualizations were generated by the authors.

Ethics statement

This study utilized aggregated sub-regional level mobility and incidence data, which did not involve human participants or identifiable private information. The requirement for ethical approval for this study and the need for informed consent was waived by the UConn Health ethics committee. All methods were carried out in accordance with relevant guidelines and regulations.

Results

Figure 2 illustrates the dynamic relationships among social distancing policy (Policy), mobility (Mobility), incidence (Incidence), and vaccination coverage (Vaccination) in the citywide VARX model. The notation .1 and .2 represent the coefficients for a 1-week and 2-week lag, respectively, indicating the impact of the previous week and two weeks ago on the current values. For example, $I.1$ represents the effect of incidence one week prior, and $I.2$ represents the effect two weeks prior.

Examining the dynamics of the citywide model, we observe that incidence and social distancing policy exhibit strong persistence over time, while mobility does not. Incidence shows a positive self-effect at a 1-week lag (I.1 = 1.24), indicating sustained transmission from the previous week, but a negative effect at a 2-week lag (I.2=-0.63), suggesting effective control mechanisms over two weeks. Social distancing policy also shows significant continuity (P.1 = 0.79), reflecting the persistence of implemented measures. In contrast, mobility lacks a significant self-effect, indicating its dependence on other variables. Social distancing policy has a significant negative association on mobility (P.1=-2.05), while mobility positively correlates with incidence in two weeks (M.2 = 2.24). This aligns with the expectations that stricter measures reduce movement and decreased contact in turn leads to lower transmission. Although social distancing policy's direct effect on incidence is not significant, its influence likely occurs indirectly through reduced mobility. Incidence significantly affects both social distancing policy (I.2 = 0.02) and mobility (I.1=-0.05), with higher cases prompting stricter measures and reduced movement. Rising vaccination coverage is significantly associated with all variables, increasing mobility

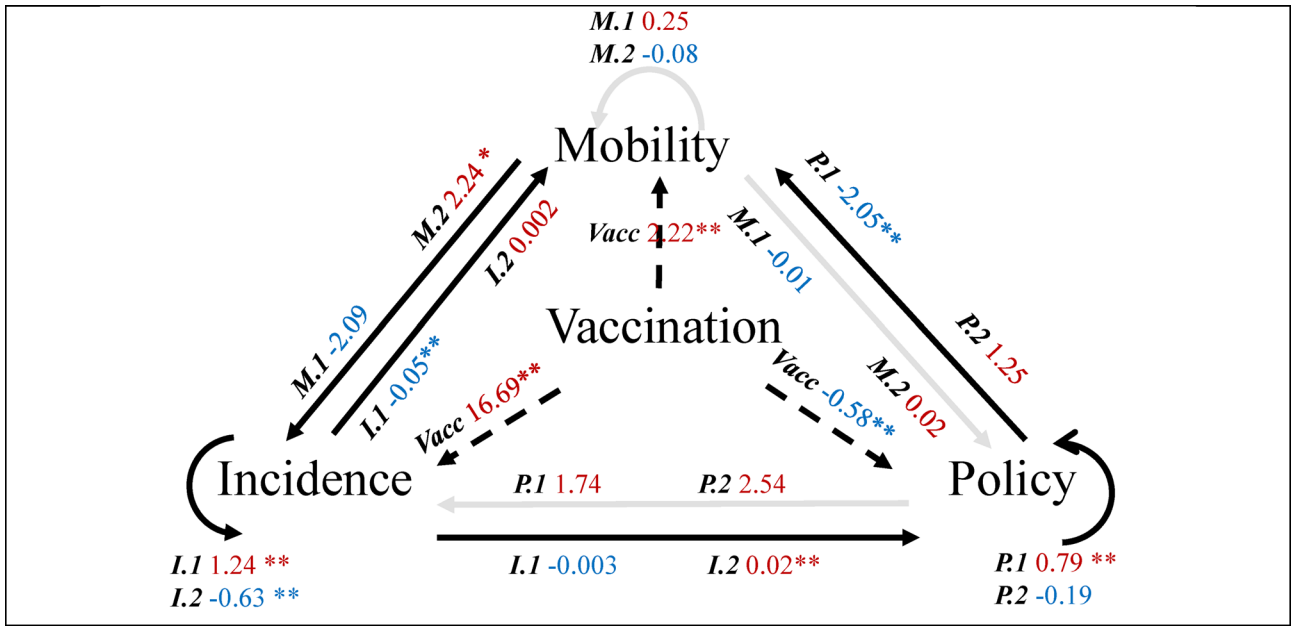


Fig. 2. Dynamic Interactions among Social Distancing Policy, Mobility, Incidence, and Vaccination Coverage in the Citywide VARX Model.

(Vacc = 2.22) and relaxing social distancing policy (Vacc=-0.58), signaling a return to normalcy. Yet, vaccination coverage shows an unexpected positive correlation with incidence (Vacc = 16.69), likely driven by the Delta variant surge during the rapid vaccination rollout in South Korea (July–November 2021).

Figure 3 illustrates the IRFs over time in a 3 by 3 matrix. The present incidence level was strongly influenced by past incidence levels (Fig. 3; Panel a) and indirectly affected by mobility (Panel b) and social distancing policy (Panel c) with time lags of ~2 weeks and ~4 weeks, respectively, likely due to reporting delays or the incubation period. Mobility was immediately reduced by increased social distancing policy stringency within 2 weeks (Panel f) and by rising incidence within 4 weeks (Panel b), reflecting the combined impact of mandatory restrictions and voluntary avoidance driven by infection fears. Social distancing policy stringency increased over a month in response to rising incidence (Panel g), and mobility showed a positive correlation with social distancing policy over time (Panel h), likely reflecting increasing mobility triggered the spread of the virus, which required a stricter social distancing policy. Overall, high incidence triggers increased social distancing policy stringency, which directly and immediately reduces mobility and indirectly decreases incidence with a time lag. This highlights the dynamic interplay between incidence, mobility, and social distancing policy during this period.

Figure 4 displays the spatial distribution of key impulse-response relationships estimated from the district-level VARX models. For each panel, districts with non-significant coefficients are shown in gray, while significant associations are color-coded by direction (red for positive, blue for negative) and intensity (darker shades represent larger absolute effect sizes). Panels A and B in Fig. 4 reveal a strong spatial overlap between the effects of mobility 2 weeks prior on current incidence (M.2 → I) and the effects of policy stringency from 1 week prior on current mobility (P.1 → M). In many commercial districts such as Gangnam-gu and Jung-gu, stringent social distancing policies significantly reduced mobility (Panel B), and reduced mobility in turn contributed to lower incidence two weeks later (Panel A). Conversely, in residential areas like Gangbuk-gu and Gwanak-gu, where policy had an insignificant impact on mobility, the mobility-incidence link also appeared insignificant. This spatial pattern suggests a sequential pathway: social distancing policies were most effective when they succeeded in curbing movement in key areas, which subsequently led to reductions in infection rates in those districts. The geographic alignment of significant effects in these two panels underscores the indirect but critical role of policy in controlling incidence via mobility reduction. Panels C and D show that while rising incidence generally led to increased policy stringency (I.2 → P) and reduced mobility (I.1 → M), the patterns diverge in key commercial areas. The effect of incidence on policy stringency is citywide and significant across nearly all districts (Panel C, mostly red), reflecting Seoul's centralized policy response to rising case counts. In contrast, the effect of incidence on mobility (Panel D) is also broadly significant but notably weaker or non-significant in major commercial districts such as Gangnam-gu and Jung-gu. This implies that in high-traffic areas, individual behavioral changes in response to rising cases—such as voluntary reduction in movement—were less pronounced, possibly due to work obligations or economic necessity. These findings indicate that while policy uniformly reacts to case surges, actual behavioral adaptation varies across space and is more evident in non-commercial districts where residents may have more flexibility to self-restrict.

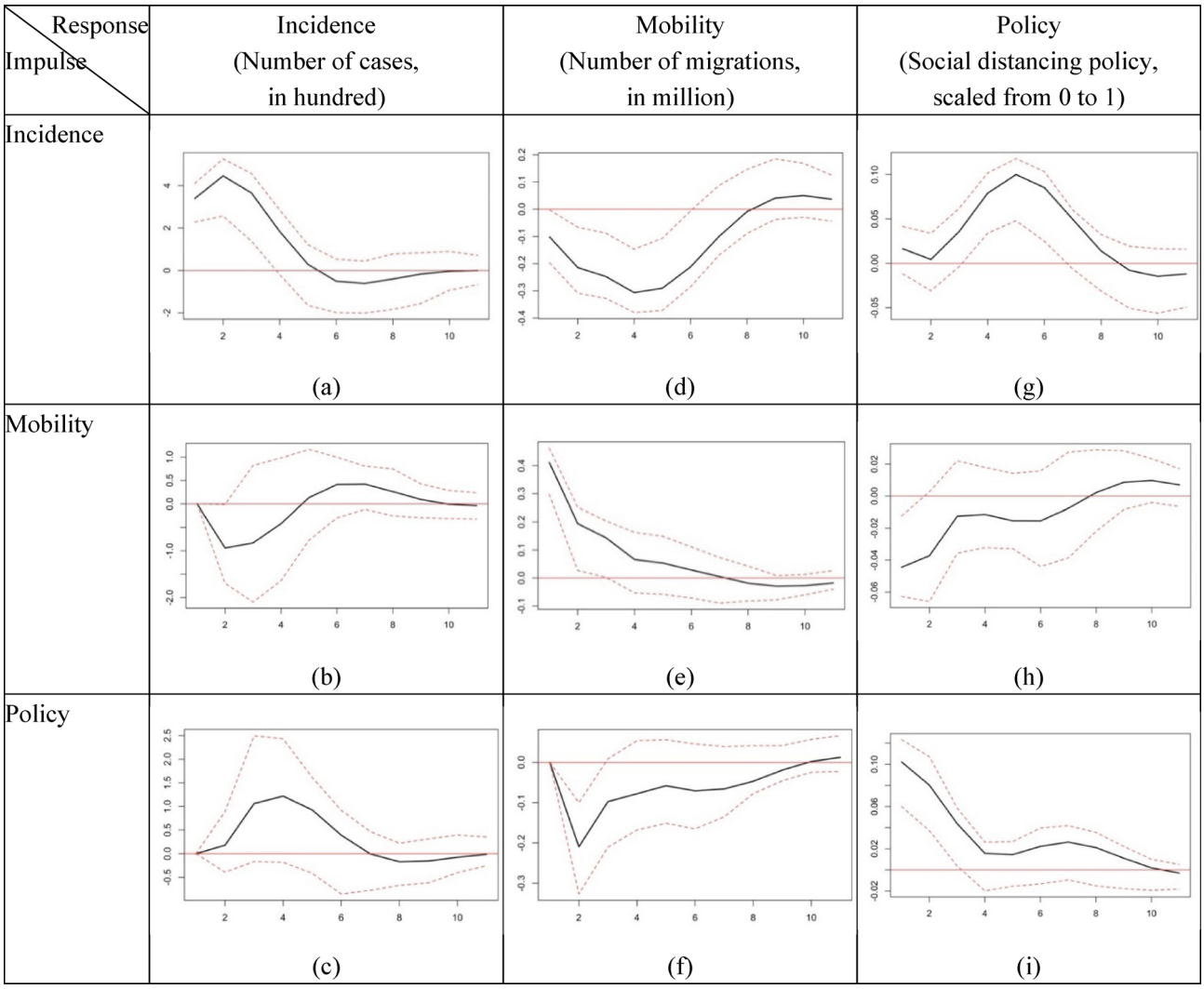


Fig. 3. Impulse Response Functions (IRFs) Matrix for Dynamic Interactions among Mobility, Incidence, and Social Distancing Policy in the Citywide Model. Notes: The dashed lines are 95% probability bands, respectively. Each small chart represents the response of a variable in a given column to a one-standard-deviation shock in a variable in a given row. The X-axis in all charts represents weeks, and the Y-axis indicates the response magnitude.

Discussion

We studied the dynamic relationship among COVID-19 incidence, mobility, and social distancing policy shocks using weekly data for 25 districts of Seoul. Our study highlights the existence of a feedback loop between mobility and incidence, with distinct patterns observed across different districts. In commercial districts, mobility and incidence tend to rise and fall together, driven by the strong direct effects of social distancing policies on both factors. In contrast, non-commercial districts exhibited more voluntary distancing behavior and peer effects, where high incidence levels led to immediate reductions in mobility. This emphasizes the critical importance of individual mobility decisions during the pandemic, shaped by a combination of mandatory social distancing policies and voluntary responses to perceived risks.

We contribute to the existing literature by empirically examining (i) the dynamic responses of infection and mobility across recurrent pandemic waves over a 16-month period, (ii) the impact of social distancing policies on infection control and mobility across different districts, and (iii) the effects of vaccination as an exogenous factor influencing these relationships. While previous studies have demonstrated that public health policies reduce COVID-19 incidence in two-factor relationships[32]our study underscores that their impact operates significantly through changes in mobility patterns. These findings also reveal general trade-offs associated with social distancing policies[33]. While such policies effectively reduce mobility, their direct impact on incidence diminishes over time.

As we transition into the COVID-19 endemic era, these findings suggest that the effectiveness of interventions will increasingly depend on local contexts, particularly in the absence of perfect enforcement capacity. Voluntary restrictions, influenced by individual perceptions of infection risk and population immunity, are likely to

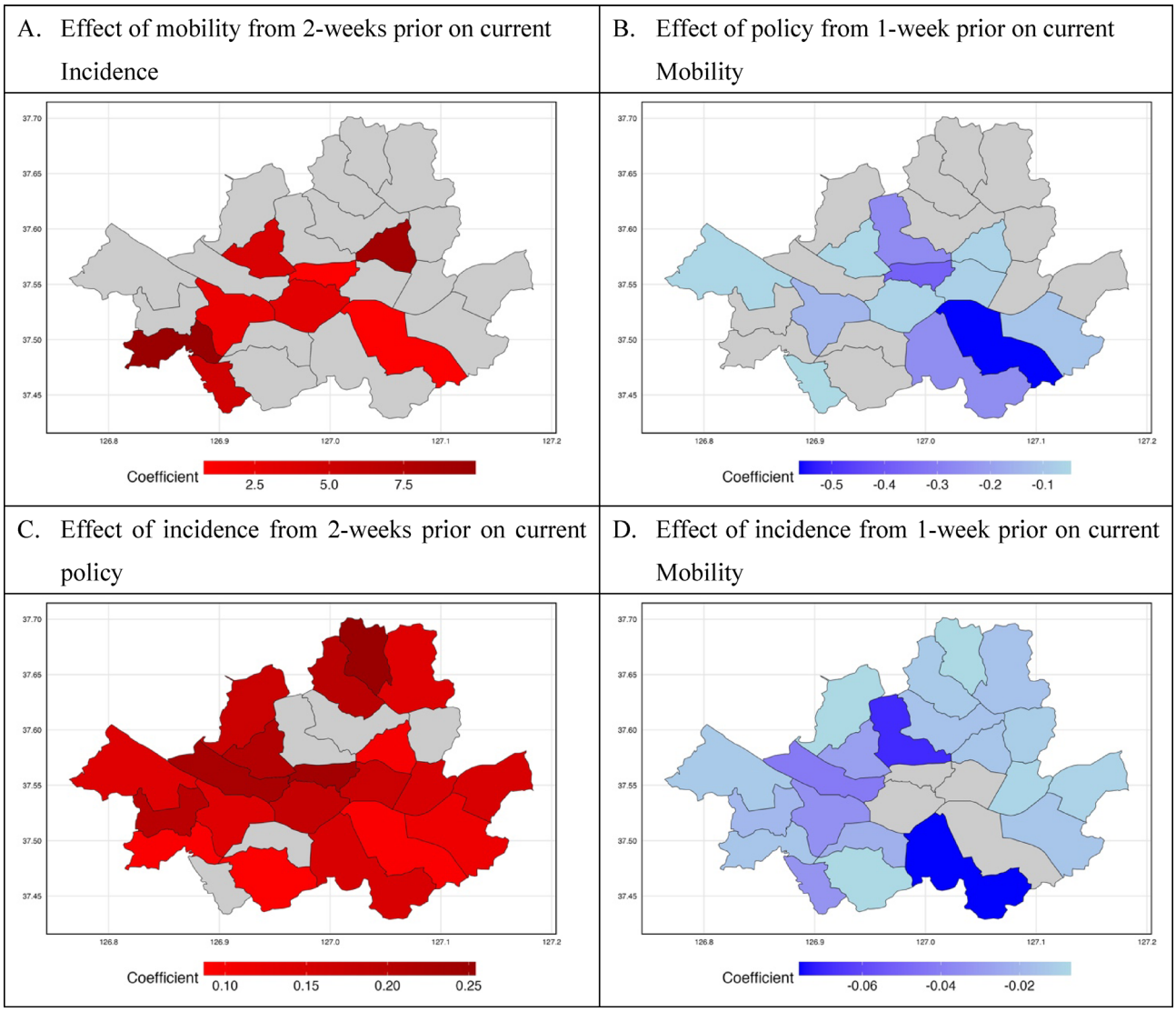


Fig. 4. Spatial Distribution of Key Coefficients in the Citywide VARX Model.

play a significant role in shaping mobility patterns. Ultimately, the effectiveness of control measures depends on individual mobility decisions, which involve balancing the risk of infection against the personal costs of disrupting daily activities. Consistent with Smith et al.[34]who demonstrated that adherence to health guidelines is significantly influenced by individuals' personal beliefs and perceived susceptibility to illness, these findings highlight the importance of addressing behavioral and informational factors in designing effective public health interventions.

Our results highlight the importance of early response and region-specific strategies to maximize the effectiveness of public health interventions while minimizing economic impacts[35–37]. In commercial districts, stringent social distancing policies are effective at controlling mobility and reducing incidence. In contrast, non-commercial districts benefit more from strategies such as localized incidence monitoring and regular testing, which encourage voluntary distancing. Our study further emphasizes that a key task for policymakers in predicting and controlling infections is to monitor changes in public perception of infection risk and compliance with health measures, as these factors vary across regions and evolve over time.

Our study has some limitations. First, the level-based standardized social distancing policy stringency measures may not fully capture the nuance and heterogeneity of government responses to COVID-19. This lack of granularity might reduce sensitivity in detecting differences in some indicators. Nonetheless, these standardized measures, based on policy stringency levels and implementation timing, enabled systematic comparisons across districts. Second, the initial four months of the pandemic (March–June 2020) were excluded from the analysis because the diverse and unstructured social distancing measures during that period could not be systematically translated into a level-based scale. During the early pandemic, particularly in March with the Wuhan variant, heightened fear of infection likely drove both voluntary and mandatory mobility restrictions. However, the overall patterns observed in our study are expected to hold, as the 16-month timeframe encompasses three major

epidemic waves[38] and accounts for evolving dynamics, including increased vaccination coverage and its impact on the relationship between mobility and disease transmission. Third, while our separate VARX models for each district with a fixed two-week lag assumption—selected based on the Bayesian Information Criterion (BIC)—enhances interpretability, it may overlook potential spatiotemporal effects if applied across long-term pandemic phases or at a broader, nationwide scale. Lag times are critical for capturing temporal dynamics, and longer lags might reveal delayed or cumulative effects, particularly in later pandemic stages. While we were unable to disaggregate the pandemic into distinct phases (e.g., early, mid, and post-social distancing) due to sample size constraints with weekly data points, future studies may consider spatiotemporal extensions of VAR[39] or phase-specific responses to social distancing policies across districts[40]considering spatially varying coefficients and lag structures. Nonetheless, we believe the current VAR approach serves as a pragmatic initial framework that can be extended or refined with spatially varying processes as data and computational resources allow. Lastly, although the upward time trend in exogenous vaccination coverage could introduce some instability into the broader system, it had a minimal impact on model fitting or forecasting in our analysis. The stability and validity of inferences among endogenous variables were confirmed through impulse response functions (IRFs) and unit root tests. Future studies could benefit from alternative methodological approaches, such as structural VAR (SVAR) models with theory-based restrictions, to better account for external shocks, like vaccination campaigns, and to identify specific causal pathways. For instance, a SVAR model could integrate restrictions informed by our findings: social distancing policies reduce mobility, which impacts incidence, while rising case numbers influence behavior by reducing mobility. This approach could address potential endogeneity and capture heterogeneous regional responses by imposing structural constraints tailored to subgroups, such as commercial and non-commercial districts.

Conclusion

We studied the dynamic impact of Covid-19, mobility, and social distancing policy. We used vector autoregressions with weekly data for 25 districts in Seoul from June 2020 to November 2021. Restrictive social distancing policy shocks lower mobility immediately, with lower cases after one week. Incidence marginally raises mobility in one week especially in noncommercial districts and mobility positively associated with incidence in two weeks, especially in commercial districts. The VARX model's ability to include district-specific time series data allows for a localized understanding of social distancing policy impacts, highlighting how different areas (e.g., commercial vs. non-commercial districts) respond to social distancing measures. This regional specificity provides practical insights for tailoring social distancing policies more effectively across diverse urban settings: in commercial districts, stringent social distancing policies can effectively control mobility and reduce the incidence, whereas, in non-commercial districts, strategies such as localized incidence monitoring and regular testing are more effective in promoting voluntary distancing. This approach offers a clearer understanding of the complex, multi-layered pathways through which social distancing policies impact COVID-19 incidence and mobility.

Data availability

The COVID-19 incidence data for this study is publicly available from Seoul Open Data Plaza (URL: https://data.seoul.go.kr/dataList/OA-20470/S/1/datasetView.do). The de-identified and aggregated mobility data for this study is purchased from SK Telecom and is available from the corresponding author on reasonable request.

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Declarations

Competing interests

The authors declare no competing interests.

Additional information

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