**Dynamic Interactions of COVID-19 Incidences, Mobility, and Policy in Seoul: A VAR Model Approach**

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**Introduction**

The Covid-19 pandemic has introduced unprecedented challenges to public health systems globally, particularly in densely populated urban areas where social interactions and mobility facilitate rapid virus transmission [1][2]. Governments responded with various stringent policy measures aimed at controlling the spread, such as lockdowns, restrictions on movement, and mandates on public behavior [3][4][5]. These policies interact with population mobility and incidences in a complex manner, particularly in large cities where high population density, intricate social structures, and diverse economic activities further exacerbate this complexity. The relationship between policy intensity, population mobility, and infection rates is not static but dynamically evolves over time. Policy adjustments are often accompanied by changes in mobility, which in turn can trigger fluctuations in infection rates, further influencing subsequent policy decisions [6]. Therefore, understanding how these factors interact and how they change across time is crucial for analyzing the dynamics of pandemic management.

Although many studies have begun to explore the dynamic relationships between policy, mobility, and COVID-19 incidences during the pandemic, there remain significant gaps. Much of the research primarily focused on the direct impact of policies on mobility [7], [8] or mobility on incidences [9], [10], [11],[12]. While these studies provide valuable insights into these pairwise interactions, they often analyze these variables in isolation, without examining the comprehensive interplay between policy, mobility, and infection rates as a dynamic and interconnected system.

While numerous studies have made substantial contributions to our understanding of the dynamic interactions between policy, mobility, and COVID-19 incidences using VAR models, certain questions remain open. For instance, d’Albis et al. provided valuable insights into the bidirectional relationship between COVID-19 incidences and mobility in France[13], yet their analysis did not incorporate policy measures as an independent variable, leaving a gap in understanding how formal interventions might alter this relationship. Gianino et al. used a VAR model and Granger causality tests to evaluate public health measures across four European countries, highlighting the context-dependent effects of policies like workplace closures on COVID-19 incidences [14]. This nuanced approach underscores the need for localized analysis but suggests further exploration of broader policy impacts might be warranted. Similarly, Camehl and Rieth effectively employed a Panel Vector Autoregression (PVAR) model to assess the macro-level impact of COVID-19, economic mobility, and containment policies across 44 countries, offering valuable cross-country perspectives on restrictive measures [15]. However, their focus on macro-level data limits insight into region- or sector-specific policy effects that might be relevant within individual urban contexts. Kim et al. innovatively applied SVAR and TVAR models in South Korea to capture the non-linear responses to social distancing and vaccination, treating vaccination as a fixed threshold to reveal its immediate impact [4]. Their study opens the door for further research on the dynamic progression of vaccination effects over time. Each of these studies adds significant value to the field and provides critical building blocks. However, questions remain about how uniform policies affect different districts within a single city and how vaccination might dynamically interact with policy and mobility trends over time—areas that our study aims to explore in greater detail.

The objective of our study is to examine the dynamic relationships between COVID-19 incidences, mobility, policy interventions, and vaccination rates in Seoul during the period of social distancing from June 2020 to November 2021. By utilizing a VARX model with vaccination rates as an exogenous variable and high-frequency weekly data, we analyze these interactions both citywide and at the district level. This dual-level approach enables us to uncover temporal patterns and causal links that might be missed in more static analyses, while also highlighting the heterogeneity in policy responses across different districts. The inclusion of vaccination rates allows us to better understand how these external factors dynamically influence the evolution of the pandemic. Policy adjustments, spikes in incidences, and vaccination campaigns exhibit varying effects over time, shaping mobility and infection rates differently in each area of the city. In a fast-changing urban environment like Seoul, such temporal and spatial analysis is essential. By comparing the overall citywide dynamics with district-specific responses, our study provides critical insights into how public health measures and vaccination efforts interact to influence the pandemic trajectory across diverse local contexts.

**Data sources.** We used four sets of data sources including district specific reported weekly COVID-19 cases from the Korea Disease Control and Prevention Agency, weekly human mobility data based on mobile phone records from SK Telecom, policy data from Korea Disease Control and Prevention Agency, and vaccination rate data from XXXXXXXX. All datasets were available between June 28, 2020, and November 1, 2021. SK Telecom is the telecommunications company with the highest number of subscribers in South Korea. Human mobility data were based on the frequency of daily movements inside and outside the areas (administrative neighborhoods “dong”), which were defined based on whether participants visited other areas outside their resident areas for at least 30 mins. Seoul metropolitan city consists of 25 autonomous districts (“gu”) and 426 administrative neighborhoods (“dong”). In order to align the mobility and incidence data, we aggregated the mobility data from dong to gu level. The policy data included three distinct levels between June 28, 2020, and November 6, 2020; five levels from November 6, 2020, to July 11, 2021; and four levels from July 12, 2021, to November 1, 2021. We standardized policy data for consistency across time periods. Given that Seoul’s policies were uniformly implemented citywide, the policy data were consistent across both city-level and district-level analyses. Vaccination data ……

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**Methodology**

**Model Overview.**

In this study, we employed the Vector Autoregression with Exogenous variables (VARX) model to analyze the interdependencies among multiple time series variables, focusing on how COVID-19 incidences, mobility patterns, and policy interventions influence each other over time in Seoul, while accounting for the effect of vaccination rates 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 policy interventions.

**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). 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 policy interventions) while incorporating the effect of the exogenous variable (vaccination rates). 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 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:

* is a vector containing the variables of interest for district at time t (e.g., COVID-19 incidences, mobility, and policy measures)
* ​ and are coefficient matrices for district , capturing the influence of past values of the endogenous variables on their current values.
* is a vector of exogenous variables (e.g., vaccination rates) for district , which influence the endogenous variables but are not influenced by them.
* is the coefficient matrix associated with the exogenous variables for district .
* represents the error terms for district , assumed to be white noise.

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

**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 policy stringency) 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:

where:

* ​is the response variable at horizon .
* ​ represents the information set before the shock at time .
* ​ is the shock applied to the impulse variable at time .

For each combination of impulse and response variables (policy, mobility, and incidences), we calculated the IRFs. In the VARX model, we also account for the effect of exogenous variables (e.g., vaccination rates), 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 policy interventions, mobility changes, and COVID-19 incidences within the system, with vaccination rates serving as an external influencing factor.

**Model Fitting and IRFs Calculation.**

We first fitted a VARX model to the variables of interest (policy, mobility, and incidence rates) while including vaccination rates 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 rates. Next, we generated shocks for each endogenous variable in the system and used the function in R 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 (), 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.

**Results**

Fig 1. Dynamic Interactions among Policy, Mobility, Incidence, and Vaccination rate in the Citywide VARX Model



Figure 1 illustrates the dynamic relationships among policy (Policy), mobility (Mobility), incidence (Incidence), and vaccination rates (Vaccination) in the citywide VARX model. The notation and 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, represents the effect of incidence one week prior, and represents the effect two weeks prior.

Examining the self-effects of the three endogenous variables, we observe that incidence and policy exhibit significant persistence over time in the citywide model. Specifically, incidence shows a positive self-effect at a 1-week lag (), suggesting that higher incidence in the previous week tends to sustain itself. However, the negative effect at a 2-week lag () indicates that incidence levels are effectively controlled after two weeks. For policy, the 1-week lag also shows a significant positive self-effect (), reflecting the continuity of policy measures over time. In contrast, mobility does not exhibit a significant self-effect, implying that it is more influenced by other variables than by its own past values.

Analyzing the inter-variable relationships, we find that policy has a significant negative impact on mobility (), indicating that stricter policy measures tend to reduce overall movement. Mobility, in turn, has a significant positive effect on incidence (), suggesting that increased mobility correlates with higher infection rates, consistent with the typical transmission dynamics of infectious diseases. However, the direct effect of policy on incidence is not significant, suggesting that policy measures might influence incidence primarily through their impact on mobility. Additionally, incidence has significant direct effects on both mobility and policy. Higher incidence leads to a notable increase on policy (), likely prompting stricter policy measures in response to worsening outbreaks. The effect on mobility is significantly negative (), indicating reduced activity as cases increase. Mobility, however, does not have a significant direct effect on policy, implying that policy adjustments may not respond directly to short-term mobility changes.

Finally, vaccination rate has a significant effect on all three variables in the citywide model. Rising vaccination rates are associated with increased mobility () and policy relaxation (), reflecting the gradual return to normalcy as vaccination progresses. Interestingly, vaccination rate shows a significant positive correlation with incidence (), suggesting that as vaccination rates increased, incidence unexpectedly rose. This effect is likely due to the entry of the Delta variant in South Korea during the period of rapidly increasing vaccination rates(July 2021 ~ November 2021), which led to a surge in cases despite the growing vaccination coverage.

Fig 2. Impulse Response Functions (IRFs) Matrix for Dynamic Interactions among Mobility, Incidence, and Policy in the Citywide Model

|  |  |  |  |
| --- | --- | --- | --- |
| Response  Impulse | Incidence  (Number of cases in hundred) | Mobility  (Number of migrations in million) | Policy  (Policy stringency, scaled from 0 to 1) |
| Incidence | **图表, 折线图  描述已自动生成** | **图表, 折线图  描述已自动生成** | **图表, 折线图  描述已自动生成** |
| Mobility | **图表, 折线图  描述已自动生成** | **图表, 折线图  描述已自动生成** | **图表, 折线图  描述已自动生成** |
| Policy | **图表, 折线图  描述已自动生成** | **图表, 折线图  描述已自动生成** | **图表, 折线图  描述已自动生成** |

Note: 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.

* **Impact of Incidence increase**: A rise of 100 new COVID-19 cases leads to an immediate reduction in mobility, with a decline of approximately 0.1 million. This initial decrease likely reflects voluntary movement restrictions by the population due to fear of infection, with the reduced mobility persisting for about four weeks before gradually returning to baseline levels. Similarly, an increase of 100 in incidence triggers an immediate tightening of policy measures. By the fifth week, policy stringency has increased by around 0.1, suggesting more severe restrictions in response to rising case numbers. After this peak in the fifth week, policy gradually relaxes, likely as case numbers stabilize or begin to decline. These dynamics demonstrate the immediate and quantifiable responses of both mobility and policy stringency to surges in COVID-19 incidence, playing a crucial role in early containment efforts.
* **Impact of mobility on Incidence**: A 1 million increase in mobility leads to an immediate decrease in incidence, followed by a delayed rise beginning around the second week. From the second to the fifth week, incidence increases by approximately 150 cases, aligning with the natural progression of disease transmission, where the incubation period creates a lag between increased exposure and visible case numbers. The initial decline in incidence could reflect temporary reporting variations or reduced susceptibility among immediately exposed individuals, with cases beginning to rise once the virus spreads further through the population. While there is a trend suggesting that higher mobility levels could contribute to increased policy stringency as a precautionary measure, this relationship is not statistically significant. This implies that although policy adjustments may sometimes coincide with periods of higher mobility, the direct effect of mobility on policy stringency is not strong enough to be conclusive, suggesting that other factors, such as rising case numbers, may play a more direct role in triggering stricter policy measures.
* **Impact of policy on mobility**: An increase in policy stringency leads to a reduction in mobility within approximately two weeks, with a decrease of around 0.2 million in mobility. This immediate impact reflects the effectiveness of social distancing measures in limiting movement. Mobility then gradually returns to baseline, taking approximately 7-8 weeks to recover fully. Although the direct effect of policy on incidence is not significant in the first two weeks, the subsequent reduction in mobility contributes to a delayed impact on incidence. Initially, incidence rates continue to rise gradually, possibly due to pre-existing exposures or transmission lag before the full effects of the policy take hold. However, by the fourth week, incidence shows a notable decline, ultimately reducing by approximately 120 cases in 3 weeks, suggesting that the policy successfully curtailed transmission over time by limiting mobility and exposure.

Fig3. District-Level Heat Map of Significant Dynamic Relationships among Mobility, Incidence, and Policy.

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Each row represents a different district, including an aggregate labeled "All districts", and each column represents different variables or lagged effects on Mobility, Incidence, and Policy, with Vaccination rate(Vacc) as an exogenous factor. The colors indicate significance and direction:

* **Red**: Positive significant relationship (dark red for 95% significance, light red for 90%).
* **Blue**: Negative significant relationship (dark blue for 95% significance, light blue for 90%).
* **Gray**: No significant relationship.
* **Mobility**: As COVID-19 cases increase, mobility significantly decreases in non-commercial districts (e.g. Geumcheon (-0.032), Dongjak (-0.022), and Yangcheon (-0.019)), likely due to heightened fear and self-restriction in response to the continuous rise in cases, with a strong negative relationship observed across multiple regions. Prior mobility levels from the previous week show no significant impact on current mobility in commercial districts, suggesting that movement in these areas may be more resilient to past trends. Policy interventions are significantly associated with reduced mobility within commercial districts (e.g. Jung (-0.375), Jongno (-0.263), and Gangnam (-0.561)), likely due to stricter enforcement and higher population density, which make compliance more impactful in these areas. Additionally, higher vaccination rates are consistently linked to increased mobility, potentially indicating greater confidence in moving freely among vaccinated populations, with a positive relationship observed across most regions (e.g. Jung (0.249), Seongdong (0.043), and Dobong(0.014)).
* **Incidence**: In some districts, COVID-19 incidences from two weeks prior are negatively correlated with current incidences (e.g. Jung (-0.590), Mapo (-0.388), and Dongdaemun (-0.494)), suggesting temporary reductions in transmission that may follow previous spikes or result from enhanced public health measures. In commercial districts, mobility levels from two weeks ago show a positive correlation with current incidences (Jung (0.797) and Gangnam (0.963)), indicating that increased mobility in the past may have contributed to subsequent transmission rates. Policy measures appear to have had minimal direct effects on current COVID-19 incidence, though they have likely influenced incidence rates indirectly by effectively reducing mobility. Vaccination rates are positively correlated with incidences, possibly due to the emergence of the Delta variant, which simultaneously increased both transmission rates and vaccination uptake.
* **Policy**: Policy measures are strongly correlated with COVID-19 incidences from two weeks prior for all districts (e.g. Jung (0.239), Mapo (0.227), and Eunpyeong (0.172)), suggesting that adjustments were reactive to earlier increases in cases. Mobility levels show no significant influence on policy changes, indicating that policy decisions were not directly driven by recent mobility patterns. There is a negative correlation exists between vaccination rates and policy stringency for most districts (e.g. Yeongdeungpo (-0.498), Guro (-0.841), and Eunpyeong (-0.421)), likely due to the gradual relaxation of policies as vaccination coverage increased, reflecting a growing confidence in population immunity.

**Conclusion & Discussion**

Our study provides comprehensive empirical evidence on the dynamic relationships between COVID-19 incidence, human mobility, and policy interventions across Seoul's districts. Through VARX analysis incorporating vaccination rates as an exogenous factor, we uncovered several significant patterns that contribute to our understanding of pandemic control mechanisms in urban environments.

The immediate decrease in mobility following rising incidence rates, particularly in non-commercial areas, demonstrates the effectiveness of public risk awareness and voluntary behavioral changes. This finding aligns with Ghader et al. (2020) [16], who documented that communities showed significant voluntary mobility reductions even before official restrictions were implemented, highlighting how informed communities can contribute significantly to epidemic control. The temporal relationship between incidence rates and policy implementation further suggests that while governments often react to case increases with stricter measures, there may be advantages to more proactive policy approaches. This observation is supported by Chen et al. (2022), who found that preventive interventions yielded better outcomes than reactive measures in controlling disease spread. Our findings reveal a consistent pattern where policy implementations typically follow two weeks after significant case increases. This reactive approach, while common, may not be optimal for epidemic control. As demonstrated by Wu et al. (2021) [17] in their comparative analysis of COVID-19 responses across multiple countries, early implementation of containment measures before substantial case escalation was associated with more effective outbreak management. This evidence suggests that governments should adopt more proactive policies, initiating preventive actions at the first signs of rising cases rather than waiting for further escalation.

Our analysis revealed distinct patterns between commercial and non-commercial districts, suggesting the need for targeted intervention strategies. Commercial areas demonstrated strong adherence to policy measures, with minimal time-lagged mobility effects, indicating effective policy compliance. However, the positive correlation between two-week-prior mobility and current incidence in these areas emphasizes the critical importance of early mobility restrictions in high-traffic zones. Meanwhile, non-commercial areas showed stronger voluntary behavior modification, suggesting that different approaches, such as regular testing and targeted public health announcements, might be more appropriate in these regions. This finding algins with the paper by Smith et al. (2021) [18], which found that individuals' adherence to health guidelines is significantly influenced by personal beliefs and perceived susceptibility to illness. The study also revealed that while policies immediately impact mobility patterns, their effect on incidence rates typically requires more than two weeks to materialize. This temporal gap between implementation and outcome, also noted by He, Shan, et al. (2021) [19] and Gianino et al.(2021) [14], underscores the importance of proactive policy deployment and sustained intervention measures. Our findings suggest that policymakers should consider this lag when designing and implementing control measures, particularly in anticipation of potential case surges.

Despite these robust findings, our study has several limitations. The generalizability of our results may be constrained by the evolving nature of the pandemic, including changes in public compliance, vaccination rates, and viral variants. Additionally, while our fixed two-week lag assumption enhanced model interpretability, it may have overlooked longer-term effects across different pandemic phases. Future research could benefit from exploring alternative methodological approaches, such as structural VAR models with theory-based restrictions or non-parametric machine learning approaches capable of capturing non-linear relationships.

The practical implications of our findings suggest that effective pandemic control requires a nuanced, region-specific approach. In commercial areas, strict mobility controls appear to be most effective, while non-commercial regions may benefit more from measures that encourage and support voluntary compliance. This differentiated approach, supported by rapid public health response systems and clear communication strategies, could enhance the effectiveness of future pandemic control efforts. These insights contribute to the growing body of evidence supporting data-driven, location-specific approaches to pandemic management. Understanding the complex interactions between human behavior, policy interventions, and disease spread is crucial for developing more effective public health strategies. Future research should continue to explore these relationships across different contexts and phases of pandemic response, particularly focusing on the long-term sustainability of behavioral changes and policy effectiveness.

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**Appendix**

**District Level coefficients**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| ***Estimation results for equation mobility:*** | | | | | | | | |
| ***incidences = incidences.l1 + mobility.l1 + policy.l1 + incidences.l2 + mobility.l2 + policy.l2 + const + trend + vaccination\_rate*** | | | | | | | | |
| DIST | Incidence.l1 | Incidence.l2 | Mobility.l1 | Mobility.l2 | Policy.l1 | Policy.l2 | Vacc\_rate |
| Total | 1.242 (0.110)\*\* | -0.632 (0.129)\*\* | -2.095 (1.263) | 2.238 (1.220)\* | 1.747 (7.290) | 2.538 (6.559) | 16.688 (5.560)\*\* |
| Jung | 1.102 (0.100)\*\* | -0.590 (0.108)\*\* | 0.016 (0.391) | 0.797 (0.391)\*\* | 0.422 (0.230)\* | 0.010 (0.204) | 0.386 (0.168)\*\* |
| Jongno | 0.905 (0.128)\*\* | -0.428 (0.130)\*\* | -1.323 (0.626)\*\* | 0.034 (0.640) | -0.135 (0.318) | -0.129 (0.275) | 0.748 (0.279)\*\* |
| Gangnam | 0.867 (0.125)\*\* | 0.024 (0.134) | -0.366 (0.488) | 0.963 (0.491)\* | -0.791 (0.583) | 0.748 (0.543) | -0.359 (0.309) |
| Yeongdeungpo | 0.504 (0.130)\*\* | 0.222 (0.142) | -1.077 (1.275) | 2.500 (1.274)\* | 0.688 (0.543) | -0.359 (0.476) | 0.928 (0.398)\*\* |
| Seocho | 0.853 (0.130)\*\* | -0.074 (0.136) | 0.211 (0.638) | 0.465 (0.636) | 0.024 (0.432) | -0.241 (0.392) | 0.172 (0.210) |
| Geumcheon | 0.548 (0.161)\*\* | -0.134 (0.180) | -0.862 (1.917) | 4.808 (1.895)\*\* | 0.463 (0.280) | -0.060 (0.269) | 1.231 (0.335)\*\* |
| Yongsan | 0.588 (0.126)\*\* | -0.054 (0.132) | -2.322 (1.684) | 3.292 (1.776)\* | 0.240 (0.384) |  | 0.023 (0.214) |
| Mapo | 1.082 (0.126)\*\* | -0.388 (0.139)\*\* | -0.579 (1.216) | 0.065 (1.241) | 0.042 (0.481) | -0.205 (0.425) | 0.309 (0.275) |
| Seongdong | 0.529 (0.133)\*\* | 0.013 (0.140) | -0.681 (1.698) | 2.418 (1.712) | 0.233 (0.379) | -0.083 (0.343) | 0.225 (0.210) |
| Dongdaemun | 0.833 (0.112)\*\* | -0.494 (0.120)\*\* | -8.239 (3.009)\*\* | 8.891 (2.993)\*\* | -0.148 (0.503) | 0.506 (0.456) | 1.702 (0.405)\*\* |
| Seodaemun | 0.667 (0.131)\*\* | 0.046 (0.158) | -2.436 (2.092) | 3.929 (2.074)\* | 0.451 (0.352) | -0.262 (0.315) | 0.111 (0.234) |
| Guro | 0.642 (0.120)\*\* | -0.101 (0.125) | -9.015 (2.796)\*\* | 9.902 (2.784)\*\* | -0.211 (0.516) | 0.577 (0.515) | 2.231 (0.581)\*\* |
| Songpa | 1.016 (0.118)\*\* | -0.507 (0.128)\*\* | -0.799 (2.460) | 1.632 (2.538) | 0.221 (0.847) | 0.142 (0.738) | 1.241 (0.531)\*\* |
| Gangseo | 0.825 (0.141)\*\* | -0.060 (0.155) | -2.703 (4.360) | 2.034 (4.054) | -0.419 (0.720) | -0.145 (0.703) | 0.825 (0.510) |
| Seongbuk | 0.699 (0.138)\*\* | -0.574 (0.152)\*\* | -8.176 (5.003) | 2.380 (4.867) | -0.097 (0.505) | -0.144 (0.487) | 2.094 (0.424)\*\* |
| Gwangjin | 0.475 (0.127)\*\* | 0.138 (0.136) | -4.049 (3.769) | 6.533 (4.178) | 0.249 (0.554) | 0.212 (0.519) | -0.004 (0.318) |
| Dongjak | 0.780 (0.127)\*\* | 0.019 (0.139) | 2.418 (2.815) | -3.052 (2.856) | 0.774 (0.434)\* | -1.157 (0.398)\*\* | 0.280 (0.229) |
| Gangdong | 0.545 (0.124)\*\* | -0.303 (0.130)\*\* | -2.378 (4.051) | 1.345 (4.109) | 0.647 (0.462) | -0.645 (0.428) | 1.585 (0.335)\*\* |
| Nowon | 0.568 (0.133)\*\* | -0.268 (0.144)\* | -2.999 (3.678) | -1.675 (3.642) | 0.059 (0.472) | -0.641 (0.451) | 1.481 (0.335)\*\* |
| Gangbuk | 0.612 (0.143)\*\* | -0.228 (0.148) | 0.276 (4.421) | -1.560 (4.387) | 0.135 (0.411) | -0.125 (0.381) | 0.978 (0.327)\*\* |
| Yangcheon | 0.782 (0.146)\*\* | -0.221 (0.167) | -0.975 (4.453) | -1.565 (4.219) | 0.263 (0.459) | -0.309 (0.443) | 0.614 (0.282)\*\* |
| Jungnang | 0.683 (0.143)\*\* | -0.208 (0.157) | -2.904 (5.560) | 0.003 (5.426) | 0.363 (0.494) | -0.353 (0.452) | 0.551 (0.316)\* |
| Dobong | 0.703 (0.122)\*\* | -0.308 (0.136)\*\* | 2.257 (3.832) | -3.408 (3.988) | 0.416 (0.338) | -0.435 (0.305) | 0.772 (0.224)\*\* |
| Gwanak | 0.822 (0.140)\*\* | -0.101 (0.145) | -6.201 (6.173) | 2.750 (6.365) | 0.220 (0.832) | -0.703 (0.785) | 0.874 (0.406)\*\* |
| Eunpyeong | 0.935 (0.145)\*\* | -0.445 (0.163)\*\* | -2.770 (4.855) | 1.384 (5.043) | 0.551 (0.472) | -0.353 (0.429) | 0.894 (0.326)\*\* |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| ***Estimation results for equation mobility:*** | | | | | | | |
| ***mobility = incidences.l1 + mobility.l1 + policy.l1 + incidences.l2 + mobility.l2 + policy.l2 + const + trend + vaccination\_rate*** | | | | | | | |
| DIST | Incidence.l1 | Incidence.l2 | Mobility.l1 | Mobility.l2 | Policy.l1 | Policy.l2 | Vacc\_rate |
| Total | -0.046 (0.014)\*\* | 0.002 (0.016) | 0.249 (0.158) | 0.075 (0.152) | -2.054 (0.910)\*\* | 1.249 (0.819) | 2.225 (0.694)\*\* |
| Jung | -0.058 (0.040) | -0.048 (0.044) | -0.035 (0.157) | -0.157 (0.157) | -0.375 (0.093)\*\* | 0.091 (0.082) | 0.249 (0.068)\*\* |
| Jongno | -0.069 (0.036)\* | -0.001 (0.036) | 0.246 (0.176) | 0.086 (0.180) | -0.263 (0.089)\*\* | 0.155 (0.077)\*\* | 0.178 (0.078)\*\* |
| Gangnam | -0.061 (0.038) | 0.028 (0.041) | 0.080 (0.148) | -0.069 (0.149) | -0.561 (0.176)\*\* | 0.093 (0.164) | 0.186 (0.094)\* |
| Yeongdeungpo | -0.033 (0.015)\*\* | -0.026 (0.017) | 0.237 (0.149) | 0.088 (0.149) | -0.140 (0.063)\*\* | 0.104 (0.056)\* | 0.143 (0.046)\*\* |
| Seocho | -0.076 (0.030)\*\* | 0.026 (0.032) | 0.120 (0.148) | 0.034 (0.148) | -0.254 (0.100)\*\* | 0.040 (0.091) | 0.074 (0.049) |
| Geumcheon | -0.032 (0.011)\*\* | -0.010 (0.013) | -0.102 (0.136) | -0.126 (0.135) | -0.048 (0.020)\*\* | 0.002 (0.019) | 0.084 (0.024)\*\* |
| Yongsan | -0.019 (0.012) | -0.003 (0.013) | 0.597 (0.160)\*\* | 0.189 (0.168) | -0.062 (0.036)\* | 0.080 (0.033)\*\* | 0.017 (0.020) |
| Mapo | -0.042 (0.016)\*\* | 0.008 (0.017) | 0.543 (0.151)\*\* | 0.251 (0.154) | -0.067 (0.060) | 0.123 (0.053)\*\* | 0.030 (0.034) |
| Seongdong | -0.015 (0.012) | -0.022 (0.012)\* | 0.287 (0.151)\* | 0.044 (0.152) | -0.069 (0.034)\*\* | 0.033 (0.031) | 0.043 (0.019)\*\* |
| Dongdaemun | -0.014 (0.005)\*\* | 0.004 (0.006) | 0.498 (0.146)\*\* | 0.134 (0.145) | -0.063 (0.024)\*\* | 0.059 (0.022)\*\* | 0.034 (0.020)\* |
| Seodaemun | -0.028 (0.010)\*\* | 0.008 (0.011) | 0.504 (0.152)\*\* | 0.100 (0.150) | -0.053 (0.026)\*\* | 0.052 (0.023)\*\* | 0.023 (0.017) |
| Guro | -0.014 (0.006)\*\* | 0.005 (0.006) | 0.664 (0.145)\*\* | -0.237 (0.144) | -0.037 (0.027) | 0.009 (0.027) | 0.041 (0.030) |
| Songpa | -0.014 (0.008)\* | -0.002 (0.009) | 0.522 (0.167)\*\* | 0.128 (0.172) | -0.103 (0.057)\* | 0.099 (0.050)\* | 0.064 (0.036)\* |
| Gangseo | -0.012 (0.005)\*\* | -0.007 (0.006) | 0.468 (0.161)\*\* | -0.020 (0.150) | -0.050 (0.027)\* | 0.032 (0.026) | 0.055 (0.019)\*\* |
| Seongbuk | -0.015 (0.004)\*\* | -0.001 (0.005) | 0.782 (0.156)\*\* | 0.120 (0.152) | -0.004 (0.016) | 0.033 (0.015)\*\* | 0.025 (0.013)\* |
| Gwangjin | -0.008 (0.005)\* | -0.002 (0.005) | 0.866 (0.144)\*\* | 0.177 (0.160) | -0.013 (0.021) | 0.059 (0.020)\*\* | -0.002 (0.012) |
| Dongjak | -0.022 (0.007)\*\* | 0.008 (0.008) | 0.691 (0.153)\*\* | 0.125 (0.155) | -0.004 (0.023) | 0.026 (0.022) | 0.011 (0.012) |
| Gangdong | -0.009 (0.005)\* | -0.001 (0.005) | 0.699 (0.163)\*\* | 0.176 (0.165) | -0.027 (0.019) | 0.047 (0.017)\*\* | 0.016 (0.013) |
| Nowon | -0.015 (0.006)\*\* | -0.002 (0.006) | 0.723 (0.153)\*\* | 0.148 (0.152) | -0.017 (0.020) | 0.043 (0.019)\*\* | 0.018 (0.014) |
| Gangbuk | -0.012 (0.005)\*\* | 0.000 (0.005) | 0.625 (0.145)\*\* | 0.166 (0.144) | -0.017 (0.013) | 0.031 (0.012)\*\* | 0.017 (0.011) |
| Yangcheon | -0.019 (0.005)\*\* | 0.006 (0.005) | 0.798 (0.139)\*\* | -0.076 (0.132) | -0.019 (0.014) | 0.027 (0.014)\* | 0.011 (0.009) |
| Jungnang | -0.011 (0.004)\*\* | 0.003 (0.004) | 0.515 (0.138)\*\* | 0.224 (0.134) | -0.011 (0.012) | 0.020 (0.011)\* | 0.007 (0.008) |
| Dobong | -0.007 (0.004)\* | -0.005 (0.005) | 0.545 (0.129)\*\* | 0.172 (0.134) | -0.015 (0.011) | 0.020 (0.010)\* | 0.014 (0.008)\* |
| Gwanak | -0.007 (0.003)\* | 0.001 (0.004) | 0.891 (0.153)\*\* | -0.096 (0.157) | -0.011 (0.021) | 0.029 (0.019) | 0.007 (0.010) |
| Eunpyeong | -0.007 (0.004)\* | 0.003 (0.004) | 0.525 (0.132)\*\* | 0.230 (0.137)\* | -0.021 (0.013) | 0.028 (0.012)\*\* | 0.006 (0.009) |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| ***Estimation results for equation policy:*** | | | | | | | |
| ***policy = incidences.l1 + mobility.l1 + policy.l1 + incidences.l2 + mobility.l2 + policy.l2 + const + trend + vaccination\_rate*** | | | | | | | |
| DIST | Incidence.l1 | Incidence.l2 | Mobility.l1 | Mobility.l2 | Policy.l1 | Policy.l2 | Vacc\_rate |
| Total | -0.003 (0.004) | 0.014 (0.004)\*\* | -0.006 (0.042) | 0.016 (0.041) | 0.785 (0.242)\*\* | -0.195 (0.218) | -0.576 (0.185)\*\* |
| Jung | -0.010 (0.105) | 0.239 (0.113)\*\* | -0.411 (0.408) | 0.049 (0.409) | 0.876 (0.241)\*\* | -0.230 (0.213) | -0.408 (0.175)\*\* |
| Jongno | 0.051 (0.112) | -0.001 (0.113) | -0.798 (0.547) | -0.348 (0.560) | 0.721 (0.278)\*\* | -0.286 (0.240) | -0.124 (0.244) |
| Gangnam | 0.031 (0.048) | 0.093 (0.052)\* | -0.173 (0.190) | -0.051 (0.191) | 0.693 (0.226)\*\* | -0.045 (0.211) | -0.275 (0.120)\*\* |
| Yeongdeungpo | 0.020 (0.058) | 0.134 (0.064)\*\* | -0.633 (0.572) | -0.184 (0.572) | 0.721 (0.244)\*\* | -0.251 (0.214) | -0.498 (0.179)\*\* |
| Seocho | 0.001 (0.077) | 0.145 (0.081)\* | -0.294 (0.378) | -0.135 (0.377) | 0.694 (0.256)\*\* | -0.102 (0.232) | -0.155 (0.125) |
| Geumcheon | 0.334 (0.123)\*\* | 0.058 (0.137) | -0.054 (1.456) | -0.003 (1.439) | 0.851 (0.213)\*\* | -0.200 (0.204) | -0.850 (0.255)\*\* |
| Yongsan | 0.080 (0.082) | 0.180 (0.087)\*\* | -2.187 (1.101)\* | 0.674 (1.161) | 0.558 (0.251)\*\* | -0.036 (0.226) | -0.186 (0.140) |
| Mapo | -0.037 (0.063) | 0.227 (0.070)\*\* | -0.329 (0.612) | -0.044 (0.624) | 0.740 (0.242)\*\* | -0.220 (0.214) | -0.339 (0.138)\*\* |
| Seongdong | 0.055 (0.083) | 0.170 (0.088)\* | -1.524 (1.067) | -0.295 (1.076) | 0.650 (0.238)\*\* | -0.091 (0.216) | -0.285 (0.132)\*\* |
| Dongdaemun | 0.011 (0.053) | 0.101 (0.057)\* | -0.744 (1.427) | -0.794 (1.420) | 0.901 (0.238)\*\* | -0.250 (0.216) | -0.410 (0.192)\*\* |
| Seodaemun | 0.140 (0.086) | 0.206 (0.103)\* | -0.237 (1.364) | -0.262 (1.352) | 0.763 (0.230)\*\* | -0.223 (0.205) | -0.429 (0.152)\*\* |
| Guro | 0.049 (0.053) | 0.094 (0.056)\* | -0.383 (1.244) | 0.563 (1.239) | 0.976 (0.230)\*\* | -0.241 (0.229) | -0.841 (0.258)\*\* |
| Songpa | -0.044 (0.035) | 0.116 (0.038)\*\* | -1.011 (0.734) | 0.276 (0.757) | 0.775 (0.253)\*\* | -0.171 (0.220) | -0.318 (0.158)\*\* |
| Gangseo | -0.023 (0.052) | 0.134 (0.057)\*\* | 0.327 (1.592) | 0.161 (1.480) | 0.947 (0.263)\*\* | -0.201 (0.257) | -0.384 (0.186)\*\* |
| Seongbuk | -0.024 (0.070) | 0.115 (0.077) | -2.431 (2.552) | -0.185 (2.482) | 0.675 (0.257)\*\* | -0.157 (0.248) | -0.236 (0.216) |
| Gwangjin | 0.076 (0.055) | 0.145 (0.059)\*\* | -1.895 (1.628) | -1.032 (1.805) | 0.579 (0.240)\*\* | -0.224 (0.224) | -0.245 (0.137)\* |
| Dongjak | 0.154 (0.077)\*\* | -0.001 (0.084) | -0.531 (1.706) | -1.483 (1.730) | 0.682 (0.263)\*\* | -0.204 (0.241) | -0.213 (0.139) |
| Gangdong | -0.114 (0.070) | 0.146 (0.074)\* | -2.866 (2.295) | -0.935 (2.328) | 0.768 (0.262)\*\* | -0.284 (0.242) | -0.139 (0.190) |
| Nowon | -0.109 (0.073) | 0.140 (0.079)\* | -1.052 (2.011) | -1.581 (1.991) | 0.896 (0.258)\*\* | -0.389 (0.246) | -0.077 (0.183) |
| Gangbuk | -0.078 (0.083) | 0.194 (0.086)\*\* | 0.249 (2.569) | -0.858 (2.548) | 1.107 (0.239)\*\* | -0.371 (0.221)\* | -0.306 (0.190) |
| Yangcheon | 0.044 (0.073) | 0.198 (0.084)\*\* | 1.242 (2.230) | -1.061 (2.113) | 0.880 (0.230)\*\* | -0.292 (0.222) | -0.351 (0.141)\*\* |
| Jungnang | 0.106 (0.069) | 0.054 (0.075) | 1.477 (2.667) | -3.602 (2.603) | 0.871 (0.237)\*\* | -0.291 (0.217) | -0.258 (0.151)\* |
| Dobong | -0.118 (0.077) | 0.254 (0.086)\*\* | -0.466 (2.418) | -3.413 (2.516) | 0.828 (0.213)\*\* | -0.257 (0.192) | -0.186 (0.141) |
| Gwanak | -0.039 (0.044) | 0.087 (0.046)\* | -1.145 (1.950) | -2.771 (2.010) | 0.793 (0.263)\*\* | -0.426 (0.248)\* | -0.122 (0.128) |
| Eunpyeong | 0.056 (0.062) | 0.172 (0.069)\*\* | 0.058 (2.061) | -2.473 (2.141) | 0.774 (0.200)\*\* | -0.313 (0.182)\* | -0.421 (0.138)\*\* |

**Lag selection**

Table S1

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Criteria | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| AIC(n) | -2.71 | -3.07 | -3.11 | -3.55 | -3.72 | -3.75 | -3.79 | -4.05 | -4.03 | -4.15 |
| HQ(n) | -2.51 | -2.74 | -2.66 | -2.98 | -3.03 | -2.94 | -2.86 | -2.99 | -2.85 | -2.85 |
| SC(n) | -2.19 | -2.24 | -1.96 | -2.10 | -1.96 | -1.67 | -1.40 | -1.35 | -1.02 | -0.83 |
| FPE(n) | 0.07 | 0.05 | 0.05 | 0.03 | 0.03 | 0.03 | 0.03 | 0.02 | 0.02 | 0.02 |

We considered four key criteria for determining the optimal lag length in our VAR model: Akaike Information Criterion (AIC), Hannan-Quinn Criterion (HQ), Schwarz Criterion (SC, also known as BIC), and Final Prediction Error (FPE). Each of these criteria offers a different perspective on balancing model fit and complexity. The AIC and FPE tend to favor models with more lags, potentially capturing more intricate relationships but also increasing the risk of overfitting. On the other hand, the HQ and SC criteria emphasize model simplicity, penalizing the inclusion of too many lags to reduce the chances of overfitting and improving model generalizability.

After evaluating all criteria, we selected a 2-week lag based on the Schwarz Criterion (SC), which is known for its conservative nature in selecting model parameters. This choice is particularly important for the VARX model, as it allows us to capture the dynamic interactions between endogenous variables (policy, mobility, and COVID-19 incidences) while accounting for the influence of exogenous factors such as vaccination rates. Furthermore, selecting a shorter lag aligns with practical considerations in pandemic studies, where the effects of policy measures, such as lockdowns or mobility restrictions, often manifest within a short time frame. Therefore, the 2-week lag strikes a balance between capturing the necessary temporal dynamics and maintaining a parsimonious model that is interpretable and relevant for analyzing the interactions between policy, mobility, vaccination rates, and COVID-19 incidence rates. Consistent with our approach, a 2-week lag was also optimal in all other regions analyzed, ensuring comparability of results.

**Unit root test**

Figure S1

图表

描述已自动生成

Roots of the characteristic polynomial:

0.6985 0.6985 0.6831 0.6831 0.6097 0.4306

The characteristic polynomial roots are derived from the coefficients of the VARX model and represent the dynamics of the time series process. Specifically, they help determine if the process is stable over time. In a stable VARX model, the influence of shocks or past values diminishes over time rather than amplifying, leading to a stationary process.

For the model to be stable, all roots of the characteristic polynomial must lie within the unit circle (i.e., have an absolute value less than one). This ensures that the time series will revert to its mean or equilibrium following a shock, rather than diverging over time. In our case, the roots all fall within the unit circle, confirming that the model is stable.

This stability check was performed across all models in each district as well, with all roots confirming stability as each root has an absolute value less than 1. This validation supports the robustness of our results and ensures that each district’s model is appropriate for interpreting long-term dynamics.