Information flow between neighboring housing markets: A case from the Seoul metropolitan area

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Abstract. This study explores the directional flow of price information within the housing market network, focusing on the Seoul metropolitan area from 2013 to 2022. Utilizing a network constructed through the multivariate Granger causality test, centrality metrics identify key industrial cities (e.g., Suwon and Hwaseong) as central nodes. In contrast, Seoul, the capital city, plays a marginal role. The findings reveal a shift in influence within the housing market network, with traditionally dominant cities like Seoul ceding prominence to key industrial hubs. Our findings suggest that spatial and industrial dynamics may now outweigh administrative hierarchy in shaping housing market centrality. Future studies should explore how external shocks have driven this transformation over time.

Keywords: Housing market network, Multivariate Granger causality test, Centrality metrics

1 Introduction

The housing market, a key driver of economic growth, requires close monitoring to promote sustainable development and prevent market distortions. A rapid housing price increase in one city can influence neighboring markets, potentially triggering housing bubbles [1]. This interdependence underscores the importance of understanding how price signals propagate across regions, particularly in densely interconnected metropolitan areas. Therefore, analyzing the directional influence of price movements, hereafter referred to as “information flow,” among adjacent housing markets is essential.

Prior studies have examined the flow of information between housing markets in regions such as the Netherlands, China, and South Korea [2–4]. In these cases, their

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capital cities—Amsterdam, Beijing, and Seoul, respectively—were identified as the most influential nodes in their national housing networks, serving as primary sources of price signals and market information. These findings underscore the pivotal role capital cities play in disseminating information across national housing markets.

Despite these valuable insights, previous research has focused primarily on major cities, often overlooking the roles of satellite cities and suburban areas in housing markets. This limitation may arise from restricted data availability for peripheral areas, challenges in modeling complex multilateral dependencies, or a historical emphasis on dominant markets like Seoul. Such gaps are increasingly relevant considering the ongoing trend of suburbanization, characterized by the expansion of business complexes in metropolitan regions of developed countries [5–7]. Therefore, analyzing the structure and hierarchy of urban housing markets requires incorporating these peripheral regions to fully capture the spatial dynamics of information flow.

To address this issue, our study examines a network of 30 cities in the Seoul metropolitan area, encompassing both central urban and suburban regions. By including these underexplored regions, our research offers a comprehensive view of inter-regional dynamics between neighboring housing markets. This broader approach allows us to investigate how spatial proximity and economic interdependencies between central and peripheral cities shape the structure of housing market networks. In moving beyond the capital-centric perspective of previous studies, this research provides a more detailed understanding of price signal propagation within metropolitan areas.

2 Data and methodology

2.1 Data

This study focuses on 30 cities within the Seoul metropolitan area, including Seoul, Incheon, and 28 cities in Gyeonggi Province. We excluded three rural counties in Gyeonggi from our analysis because of their illiquid housing markets and limited apartment presence [8].

Figure 1 illustrates the study sites where apartment price indices are analyzed, as apartments represent the predominant housing type in South Korea [9]. The dataset, sourced from the Korea Real Estate Board, covers the period from January 7, 2013, to May 9, 2022, and includes 488 weekly observations per city.

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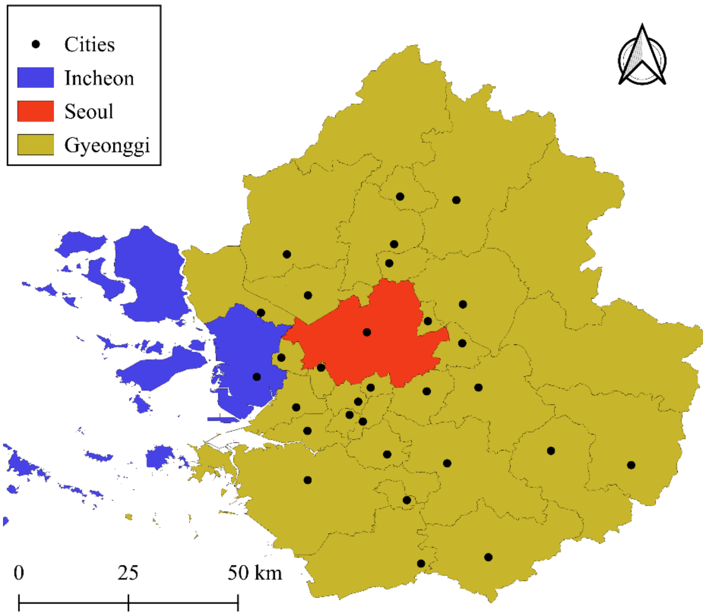

Fig. 1. Seoul metropolitan area. Bounded regions marked with black dots indicate the 30 cities included in this study.

2.2 Multivariate Granger causality test

The Granger causality (GC) test [10] evaluates whether one time series can predict another by determining if the past values of one time series improve the other's predictions. However, the pairwise nature of this approach may exclude relevant variables, potentially leading to spurious results.

The multivariate GC (MVGC) test [11] addresses this limitation by incorporating multiple variables. This allows for a more robust analysis in multivariate systems. Unlike the traditional GC method, MVGC examines how one set of variables influences another while accounting for complex interactions among all variables. This capability makes it especially effective for studying interconnected systems with multiple pathways. In the MVGC framework, the vector autoregressive model expands to include multiple time series, represented as $X_t = (x_{1,t}, x_{2,t}, x_{3,t}, \ldots, x_{n,t})'$. Here, n represents the number of different time series data considered. The multivariate form of the model can be expressed as follows:

$$X_t = \sum_{i=1}^{p} B_i \; X_{t-i} + \epsilon_t. \tag{1}$$

Here, B_i is the $n \times n$ coefficient matrix for the lag i vector, and ϵ_{t} is the $n \times 1$ error vector. The MVGC test assesses whether the past values of one series (e.g., $x_{2,t}$) enhance another (e.g., $x_{1,t}$) series' predictions while considering the influence of other series in the system (e.g., $x_{3,t}, x_{4,t}, \ldots, x_{n,t}$). The lag order ($p$) is determined using the Akaike information criterion [12].

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Conditioned on $x_{3,t}, x_{4,t}, x_{5,t}, \ldots, x_{n,t}$, the null hypothesis of the MVGC test posits that the past values of $x_{2,t}$ provide no additional predictive power for $x_{1,t}$. We defined the F-statistic as follows:

$$F_{x_{2,t} \to x_{1,t} \mid \{x_{3,t}, x_{4,t}, \ldots, x_{n,t}\}} = \frac{m - p(n+1)}{pn_y} \cdot \frac{|\Sigma'_{xx}|}{|\Sigma_{xx}|}. \tag{2}$$

Here, m is the number of observations, and n_y is the dimension of $x_{2,t}$. Σ_{xx} is the residual covariance matrix from the unrestricted model, and Σ'_{xx} is from the restricted model. A larger F-statistic exhibits a greater reduction in prediction error when $x_{2,t}$ is included, and this reflects a stronger causal relationship [11]. Therefore, we used the F-statistics from the MVGC tests to determine the node weights within the information network of the Seoul metropolitan housing market.

2.3 Centrality metrics

Centrality metrics quantify a node's influence within a network [13–16]. This study employs several key metrics: degree centrality [17,19], hub and authority scores [18], and eigenvector centrality [19,20].

Degree centrality. In a graph $G(V, E)$, with vertex set V and edge set E, degree centrality quantifies a node's connectivity [15,16]. In weighted networks, degree centrality is calculated as the sum of edge weights instead of the number of connections. For directed graphs, degree centrality is divided into out-degree (activity) and in-degree (popularity). The out-degree centrality of node i is as follows:

$$D_{out}(i) = \sum_j w_{ij} m_{out}(i, j). \tag{3}$$

Here, w_{ij} is the edge weight from node i to j, and $m_{out}(i, j)$ equals 1 if such an edge exists and 0 otherwise. Similarly, in-degree centrality is as follows:

$$D_{in}(i) = \sum_j w_{ji} m_{in}(i, j). \tag{4}$$

Here, $m_{in}(i, j)$ is 1 if an edge exists from node j to i and 0 otherwise.

Hub and authority scores. Derived from eigenvector centrality, hub and authority scores capture the mutually reinforcing relationship between nodes. Authority scores assess a node's importance, while hub scores measure its connections to authority nodes. Hub nodes link to numerous authority nodes, and authority nodes are heavily linked by many hubs. Both of these scores are iteratively computed, with numerical weights updated for each node [17].

Eigenvector centrality. Eigenvector centrality measures a node's influence by considering both its connections and the importance of its neighbors [20,21]. This is defined as follows:

$$E(i) = \frac{1}{\lambda} \sum_{j=1}^{n} A_{ij} E(j). \tag{5}$$

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Here, λ is the eigenvalue scaling the centrality scores, and A_{ij} is the weighted adjacency matrix for a network with n nodes. Nodes with high eigenvector centrality are linked to other highly central nodes.

3 Results and discussion

Table 1 presents the centrality metrics for cities in the Seoul metropolitan area, emphasizing the three cities with the highest values for each metric. The findings underscore the prominent roles of populous cities in the Seoul metropolitan housing market network. Among Gyeonggi Province's cities, Suwon and Hwaseong emerge as key players. Suwon ranks highly in in-degree, authority, and eigenvector centrality, reflecting its position as a major recipient of housing price signals. By contrast, Hwaseong ranks highest in out-degree and hub scores, indicating its role as a key source of influence. Hence, Suwon functions as a central information receiver and connector. Conversely, Hwaseong is the network's strongest information transmitter. This distinction may be attributed to the presence of Samsung Electronics' headquarters and factories [22,23]. Similarly, Yongin, where SK Hynix leads the development of a semiconductor cluster, serves as another influential node transmitting information across the network. These industrial hubs, anchored by national industries, experience high residential demand [24], reinforcing their critical roles in the housing market network.

Table 1. Centrality metrics of cities in the metropolitan Seoul area. The bracketed values represent centrality metrics (rounded to two decimal places) that are calculated based on edge weights obtained from the F-statistics of the MVGC test.

Rank	1	2	3
In-degree	Suwon [0.40]	Yangju [0.21]	Paju [0.20]
Out-degree	Hwaseong [0.26]	Yongin [0.24]	Dongducheon [0.20]
Authority	Suwon [1]	Pyeongtaek [0.27]	Gunpo [0.23]
Hub	Hwaseong [1]	Yongin [0.62]	Incheon [0.33]
Eigenvector	Suwon [1]	Gimpo [0.76]	Yangju [0.75]

Among the two most populous cities, Incheon and Seoul, contrasting roles are evident. Incheon, bolstered by aviation and biotechnology industries [25], exhibits a high hub score, reflecting industrial activities and national economic development initiatives. Conversely, Seoul—despite being the region's largest city and its most economically dominant (contributing 22.6% of South Korea's GDP in 2013 [26])—plays a surprisingly marginal role within the network. Specifically, Seoul ranks 20th for in-degree centrality, 19th for out-degree centrality, 22nd for authority, 26th for hub score, and 14th for eigenvector centrality. Similarly, first-phase new towns in Gyeonggi Province, including Goyang, Seongnam, and Bucheon [27,28], demonstrate limited influence. These findings suggest a shift in the roles of traditionally dominant cities in the housing market network during the study period. This shift is likely influenced by

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structural changes in the market caused by external shocks, such as administrative regulations [29] and economic crises [30].

4 Conclusion

This study employed the MVGC test and centrality metrics to analyze the information flow among housing markets in 30 cities within the Seoul metropolitan area. Our results indicate a diminished role for Seoul and other historically dominant cities, underscoring a shift in centrality toward key industrial cities such as Suwon and Hwaseong.These findings are counterintuitive, given existing literature that emphasizes the leading role of capital cities in housing market networks. The results suggest that external shocks, such as policy changes or economic crises, may have altered the information dynamics within the Seoul metropolitan housing market network, warranting further exploration in future research.

Future studies should explore why the findings of this research diverge from previous literature, particularly regarding temporal dynamics. Period-specific analyses could help identify whether external events (e.g., political shifts or the COVID-19 pandemic [31]) have reshaped the structure of information flow. These insights could further inform policy discussions on how government interventions should be tailored to address the evolving dynamics of regional housing markets.

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