# A Multilayer and Temporal Network for Studying the Connections of Cross-listed Stocks

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**Abstract.** Multilayer networks are increasingly used to capture complex relationships in financial systems. In this paper, we employ a multilayer and temporal network framework to analyze dynamic connections among cross-listed stocks. Each network layer corresponds to a distinct market, and a rolling window approach tracks the temporal evolution of connections, particularly during market shocks. To compare the roles of cross-listed firms in the two markets, we design a centrality imbalance indicator. Community detection is used to reveal hidden structures based on this indicator. The analysis shows that stocks from the same firms exert different levels of influence, and the key stocks in both A-shares and H-shares always shift. The connections can be significantly enhanced during periods of financial stress. Notably, community detection results indicate that differences in cross-listed firms' importance may be linked to how strongly the corresponding stocks are connected. This study extends the application of multilayer and temporal network models to financial markets, offering a systematic approach to analyze evolving market relationships and their implications for financial risk.

**Keywords:** Multilayer Network, Temporal Network, Community Detection, Cross-listed Stocks, Centrality Imbalance.

## 1 Introduction

As capital markets continue to globalize, cross-listing has become a prevalent strategy for firms seeking to broaden their investor base and access capital. A natural linkage exists between the cross-listed shares, as they represent claims on the same underlying entity. However, this linkage is further shaped by institutional differences across markets and limited information transparency. The connections between cross-listed stocks exhibit highly complex characteristics [6,8]. Therefore, a deeper investigation into the connections of cross-listed stocks and their dynamic evolution can contribute to a better understanding of inter-market linkages, providing a new foundation for asset pricing and market efficiency theories.

Prior research on cross-listed equities has focused on their pricing relationships, primarily from the perspective of cointegration and causality [5,9,10,12]. However, these studies tend to deal with such linkages in isolation from the broader market context. Yet, financial markets are complex systems where most assets exhibit some degree of

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interdependence [13]. The complexity of cross-listed stock linkages may extend beyond the scope captured in earlier literature. This raises important but underexplored questions: whether these stocks exhibit similar behaviors or influence in their respective markets? And how do their connections change facing with market shock? Addressing these questions requires a shift toward a more network-oriented and dynamic analytical approach.

A multilayer network consists of multiple layers, each representing distinct types of nodes or relationships [7,17]. This structural richness enables a more comprehensive understanding of complex interactions than single-layer network models. Consequently, this method can offer a more informative representation of financial system complexity by preserving the diversity of nodes, edges, and structural patterns [11,19]. For example, Bargigli observed that the layers of financial multilayer networks differ in structure, and that connections between nodes are not equally stable across layers [3]. In addition, temporal network analysis further contributes to understanding how these structures evolve over time, allowing researchers to capture changes in connection patterns during different market conditions.

In this paper, we first construct a multilayer network based on the correlation of cross-listed stock returns, where each market is represented as a network within a layer. To extract meaningful and sparse connections, we apply the Planar Maximally Filtered Graph (PMFG) method. Next, we employ a rolling window approach to examine the structure of the temporal network, with particular attention to changes during market shock. This analysis reveals the evolving role of cross-listed stocks in spreading information across markets. In the final stage of our analysis, we examine how stocks from the same firm behave across different layers of the network. To quantify their different levels of influence, a centrality imbalance indicator is constructed. Based on this indicator, we apply the Louvain algorithm to detect communities. The results identify several groups of cross-listed firms that display diverse behavioral patterns across markets.

The rest of this paper is organized as follows: In section 2, we review the data source and the methodology for network construction and measure. In section 3, we present the connection dynamics of cross-listed stocks. In section 4, we describe the process and findings of community detection. Finally, in section 5, we summarize and conclude the paper.

## 2 Methodology

In this section, we begin with a description of the data source, then proceed to the construction of the multilayer network and the measurement of relevant topological indicators.

### 2.1 Data Source

As China's capital markets have gradually liberalized, more domestic firms have opted for dual listings in both the Shanghai/Shenzhen and Hong Kong stock exchanges. The expansion of cross-border connectivity has also enhanced trading efficiency and

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liquidity of equities. In addition, the persistent premium observed in cross-listed A-shares has long drawn attention, with numerous investors actively seeking arbitrage opportunities [2,14,20]. This enduring phenomenon highlights the significance of studying A+H stocks, as the insights derived from such analyses can offer valuable perspectives on cross-listing dynamics in both emerging and developed markets.

To construct a clean and reliable dataset, we limit our sample to firms that had already achieved cross listings prior to 2013. Daily closing prices for these A+H shares were collected from the Wind database from the last trading day of 2012 to the end of October 2023. In processing the data, we first removed any stock pairs with non-overlapping trading calendars between the two markets. Next, we excluded pairs where trading was suspended for more than 100 consecutive days on either exchange. After these filters were applied, the final sample consists of 72 A+H stock pairs. Table 1 presents the codes for all cross-listed A+H stocks included in the analysis.

**Table 1.** List of cross-listed A+H stocks.

| Index | A-stock code | H-stock code | Index | A-stock code | H-stock code |
|---|---|---|---|---|---|
| 1 | 000898 | 00347 | 37 | 600871 | 01033 |
| 2 | 600332 | 00874 | 38 | 601107 | 00107 |
| 3 | 601588 | 00588 | 39 | 600012 | 00995 |
| 4 | 002594 | 01211 | 40 | 000338 | 02338 |
| 5 | 000488 | 01812 | 41 | 601336 | 01336 |
| 6 | 600874 | 01065 | 42 | 000756 | 00719 |
| 7 | 601991 | 00991 | 43 | 600188 | 01171 |
| 8 | 600875 | 01072 | 44 | 601038 | 00038 |
| 9 | 002672 | 00895 | 45 | 601633 | 02333 |
| 10 | 600196 | 02196 | 46 | 600036 | 03968 |
| 11 | 601398 | 01398 | 47 | 002703 | 01057 |
| 12 | 601238 | 02238 | 48 | 600115 | 00670 |
| 13 | 601333 | 00525 | 49 | 601111 | 00753 |
| 14 | 600585 | 00914 | 50 | 601800 | 01800 |
| 15 | 600837 | 06837 | 51 | 601318 | 02318 |
| 16 | 000921 | 00921 | 52 | 601628 | 02628 |
| 17 | 600027 | 01071 | 53 | 601088 | 01088 |
| 18 | 600011 | 00902 | 54 | 600028 | 00386 |
| 19 | 601939 | 00939 | 55 | 601857 | 00857 |
| 20 | 600362 | 00358 | 56 | 601601 | 02601 |
| 21 | 601328 | 03328 | 57 | 601186 | 01186 |
| 22 | 002202 | 02208 | 58 | 601988 | 03988 |
| 23 | 601992 | 02009 | 59 | 601766 | 01766 |
| 24 | 601880 | 02880 | 60 | 601390 | 00390 |
| 25 | 603993 | 03993 | 61 | 601618 | 01618 |
| 26 | 600808 | 00323 | 62 | 601808 | 02883 |
| 27 | 600016 | 01988 | 63 | 000039 | 02039 |

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| | | | | | |
|---|---|---|---|---|---|
| 28 | 600029 | 01055 | 64 | 000157 | 01157 |
| 29 | 600775 | 00553 | 65 | 601898 | 01898 |
| 30 | 600377 | 00177 | 66 | 601998 | 00998 |
| 31 | 601288 | 01288 | 67 | 600030 | 06030 |
| 32 | 600600 | 00168 | 68 | 000063 | 00763 |
| 33 | 002490 | 00568 | 69 | 601866 | 02866 |
| 34 | 600688 | 00338 | 70 | 601919 | 01919 |
| 35 | 601607 | 02607 | 71 | 600026 | 01138 |
| 36 | 600548 | 00548 | 72 | 601899 | 02899 |

**Notes:** For clarity and consistency in later sections, we assign simplified identifiers to each stock based on its listing market and the index number shown in Table 1. For example, "A1" and "H1" refer to the A- and H-share of the first listed company in the sample, with stock codes "000898" and "00347", respectively.

### 2.2 Network Construction

The multilayer network framework consists of two intra-layer networks, corresponding to the A-share and H-share markets, respectively. Each layer captures the internal structure and interaction patterns within markets. This design allows us to preserve market-specific topological features while enabling a parallel comparison of cross-listed stocks within their respective trading environments.

**Connection Measures.** The return of stock $i$ on day $t$ is calculated as the natural logarithmic difference of its closing prices on two consecutive trading days, defined as:

$$R_i(t) = \ln(P_i(t)) - \ln(P_i(t-1)) \tag{1}$$

Based on the time series of log returns, we use the Pearson coefficient to measure the connections between cross-listed stocks. which reflects the linear association between their return fluctuations. The corresponding formula is given by:

$$c_{ij} = \frac{\langle R_i R_j \rangle - \langle R_i \rangle \langle R_j \rangle}{\sqrt{\left(\left\langle (R_i)^2 \right\rangle - \langle R_i \rangle^2\right)\left(\left\langle (R_j)^2 \right\rangle - \langle R_j \rangle^2\right)}}. \tag{2}$$

Here, $\langle \ \rangle$ denotes the temporal average across all trading days. Thus, we can obtain the connection matrix of A- and H-share markets separately.

**Multilayer Network Framework.** Using the connection matrices above, we can establish a multilayer network. Specifically, each market is modeled as an independent network layer, indexed by $\alpha = 1, 2$, corresponding to the A- and H-share markets. The multilayer network is defined as a graph $G^\alpha = (V^\alpha, E^\alpha)$, where $V^\alpha = \{v_1^\alpha, ..., v_N^\alpha\}$ denotes the set of nodes, with each node representing an individual stock traded in that market. The edge set $E^\alpha \subseteq V^\alpha \times V^\alpha$ captures the connections among stocks within the same market layer, as inferred from their pairwise correlation strengths.

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**Multilayer Network Filtering.** The initial multilayer network derived from the pairwise connection matrices is dense with edges linking every pair of nodes. To reduce network complexity, we apply the Planar Maximally Filtered Graph (PMFG) algorithm. This technique preserves the most significant relationships under the constraint of planarity, allowing us to uncover the underlying topological structure while eliminating redundant links [15,18].

### 2.3 Network Measures.

This study utilizes multiple metrics to analyze both the global and local structures within the multilayer network. All metrics are classified into two types: market-level and stock-level.

**Market-level Measures.** To quantify the overall degree of connectivity within different markets, we calculate the Average Connection Strength (ACS). This metric reflects the mean edge weight across all node pairs in layer $\alpha$, and is expressed as:

$$ACS^{\alpha} = \frac{1}{2N}\sum_{i=1}^{N}\sum_{j=1, j\neq i}^{N} c_{ij}^{\alpha}. \tag{3}$$

To evaluate the structural similarity between two network layers, we adopt a similarity measure that captures the proportion of shared connections. Specifically, we follow the approach of Aldasoro and Alves [1], employing the Jaccard index to quantify the overlap of edges, i.e., the degree of substitutability between layers. The definition is given as follows:

$$J\left(G^{\alpha}, G^{\beta}\right) = \frac{\left|G^{\alpha} \cap G^{\beta}\right|}{\left|G^{\alpha} \cup G^{\beta}\right|}. \tag{4}$$

**Stock-level Measures.** Within each network layer, the degree of a node quantifies the total number of direct connections it maintains with other nodes. For node $i$ in layer $\alpha$, the degree is computed as::

$$k_i^{\alpha} = \sum_{j=1,}^{N} A_{i,j}^{\alpha}. \tag{5}$$

Here, $A_{i,j}^{\alpha}$ is the adjacency matrix in network layer $\alpha$.

Closeness centrality captures how quickly a node can interact with others, based on the average length of the shortest paths connecting it to all other nodes in the same layer. For a given node $i$, the closeness centrality is computed as:

$$C_{c}^{\alpha}(i) = \frac{N-1}{\sum_{j=1, j\neq i}^{N} d(i,j)^{\alpha}}. \tag{6}$$

Here, $d(i,j)^{\alpha}$ represents the shortest path distance between two nodes. A higher value implies stronger accessibility and potential influence within the network.

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Betweenness centrality evaluates how frequently a node functions as an intermediary in the shortest connection paths among all other node pairs. For a given node $i$, its betweenness centrality is defined by:

$$b^{\alpha}(i) = \sum_{f \neq i \neq d, f<d} \frac{g_{fd}^{\alpha}(i)}{g_{fd}^{\alpha}}. \tag{7}$$

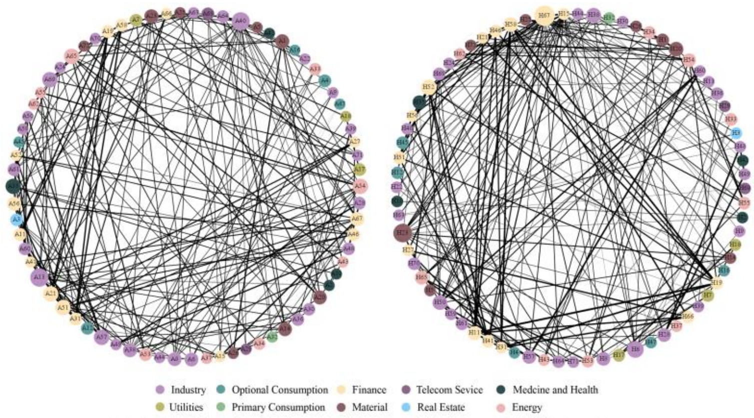
Here, $g_{fd}^{\alpha}$ represents how many times it lies on the shortest paths between all possible node pairs. $g_{fd}^{\alpha}(i)$ is the number of those paths that go through node $i$.

Eigenvector centrality is used to measure how important a node is by not only counting its connections, but also considering how important its neighbors are. A node gets a higher score if it is connected to other well-connected nodes. For a given node $i$, its eigenvector centrality is defined by:

$$C_e^{\alpha}(i) = \frac{\sum_{j=1}^{N} A_{i,j}^{\alpha} C_e^{\alpha}(j)}{\lambda}. \tag{8}$$

Here, $\lambda$ stands for the eigenvalue and $e$ refers to its associated eigenvector of $A_{i,j}^{\alpha}$.

## 3 Result and Discussion




(a) A-share layer (b) H-share layer

**Fig. 1.** Static multilayer network of cross-listed A+H stocks.

To better understand the structure of the multilayer network, we created a static network of cross-listed stocks using Python, as shown in Fig. 1. In the figure, node size reflects its degree, while thicker edges imply stronger connections between nodes. Color indicates the firm's industry category, classified according to the standards of the China Securities Index Company. Overall, we observe a noticeable pattern of industry concentration within both layers. This tendency may arise from the fact that firms operating in the same sector often maintain close business relationships and are subject to similar regulatory or policy environments. Such common exposures can lead to stronger

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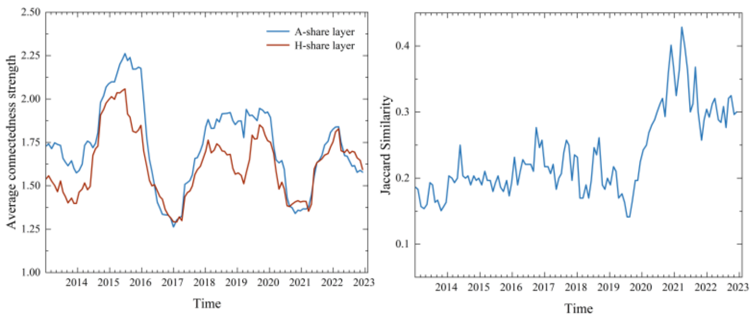
connections among industry peers. Furthermore, the filtered A-share and H-share networks display distinct internal link structures, highlighting differences in how firms interact within each market.

To capture the dynamic features of cross-listed stock connections, we adopt a rolling window approach to construct temporal network. Specifically, the time window spans 200 trading days and moves forward in increments of 20 trading days. This setup allows us to track gradual changes in network structure over time.

### 3.1 Market-level Analysis.

Fig. 2(a) illustrates the changes in Average Connectedness Strength (ACS) over time within the network layers corresponding to A-shares and H-shares. It can be observed that, in most periods, the ACS in the A-share network remains consistently higher than that of the H-share network, suggesting that A-share stocks exhibit stronger connections. This pattern may reflect underlying differences between the two markets, such as investor composition, liquidity, and regulatory frameworks.




(a) ACS of A- and H- share layer (b) JS between A- and H- share layer

**Fig. 2.** Time-varying Average Connection Strength and Jaccard Similarity.

As shown in Fig. 2(a), the ACS in both layers exhibits a similar trend across the entire period. This situation implies that despite structural differences, the two markets often respond to external shocks in a similar manner. Several notable surges in the ACS curves appear to coincide with key global and domestic events. In mid-2015, the sharp rise and subsequent crash of the Chinese stock market is reflected in a pronounced peak in both layers. Another visible rise occurs around 2018, corresponding to the trade conflicts between China and the United States. The onset of the COVID-19 pandemic in early 2020 and the outbreak of the Russia-Ukraine conflict in 2022 also align with significant increases ACS. These patterns suggest that during periods of market shocks—whether due to economic disruptions, political conflicts, or health emergencies—the cross-listed stocks tend to exhibit stronger interdependence within each market. As such, the ACS may serve as a signal of systemic stress, offering valuable insights for both market participants and policymakers monitoring financial stability.

Fig. 2(b) displays the evolution of the Jaccard similarity between the A-share and H-share layers over time. A gradual upward trend is evident, indicating that the structural

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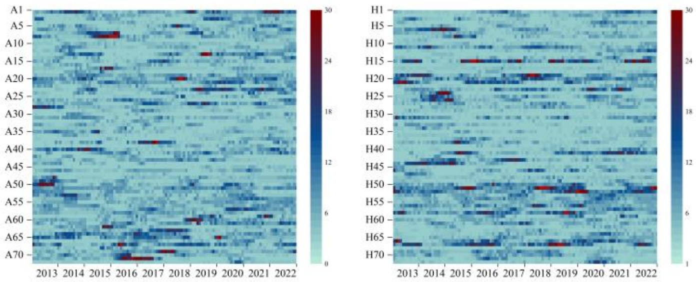
overlap between the two layers has increased throughout the sample period. This rising similarity may reflect the development of cross-border trading frameworks between Mainland China and Hong Kong. Notably, the introduction of the Shanghai-Hong Kong Stock Connect in 2014, followed by the launch of its Shenzhen counterpart in 2017, marked important milestones in market integration. These initiatives expanded the tradable stock universe and promoted interaction between the two markets, contributing to the modest increase in network similarity. Since 2020, the Jaccard similarity values have fluctuated within a higher range (approximately 0.2 to 0.4), suggesting that connections within A-share and H-share markets have become more aligned. This may result from both institutional improvements and the growing linkage between domestic and global capital markets. Similar conclusions were drawn by Cai et al. [4], who argued that policy reforms can enhance pricing efficiency in A+H stocks, thereby promoting structural convergence across markets.

### 3.2 Stock-level Analysis.

To further investigate the behavior of cross-listed stocks , Fig. 3 visualizes the temporal dynamics of node degree for each stock. Warmer colors (closer to red) represent higher node degrees, indicating a more central position in the network. The heatmaps clearly show that the degree of most nodes fluctuates significantly over time, reflecting that the role or influence of cross-listed stocks in the network is not fixed. In other words, a stock's importance within a market evolves along with changes in external conditions such as market sentiment or macroeconomic shocks. Moreover, the node degree patterns of many paired stocks differ noticeably between two layers, even during the same time period. This highlights the different levels of influence despite the fact that both stocks originate from the same firm. Such variance suggest that investors should monitor the role of each listing separately and adjust their strategies dynamically .




(a) Dynamic node degree in A-share layer (b) Dynamic node degree in H-share layer

**Fig. 3.** Time-varying node degree in A-share and H-share layers.

Figs. 4-6 illustrate the temporal evolution of stock-level centrality measures, including closeness, betweenness, and eigenvector centrality. Consistent with the findings in Fig. 3, we observe different performances in the same centrality metrics of cross-listed paired stocks. However, for some individual cross-listed stocks, their three centrality metrics exhibit consistent importance during the same period, such as A40 (i.e.,

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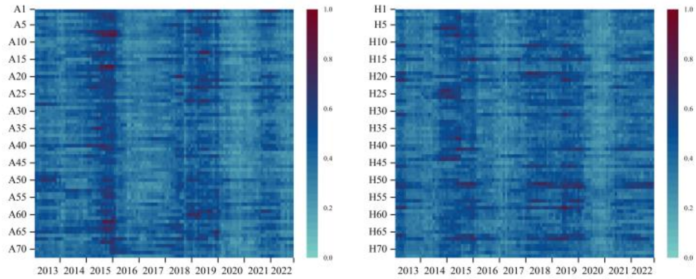
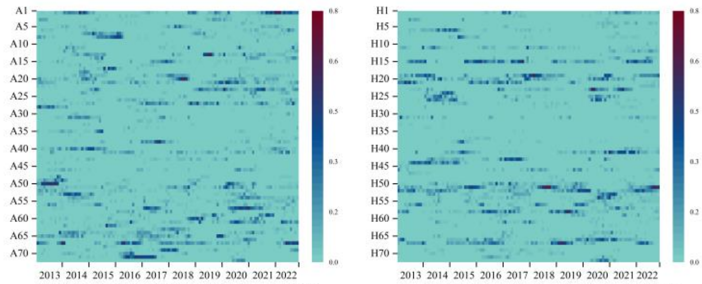
000338) and H15 (i.e., 06837). This indicates that these cross-listed stocks often hold central positions in their respective markets. They tend to act as key channels for information flow, reacting quickly to external shocks and linking otherwise separate parts of the network.



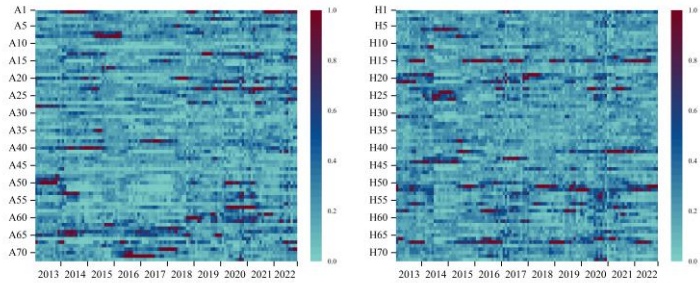

(a) Dynamic Closeness Centrality in A-share layer (b) Dynamic Closeness Centrality in H-share layer

**Fig. 4.** Time-varying closeness centrality in A-share and H-share layers.




(a) Dynamic Betweenness Centrality in A-share layer (b) Dynamic Betweenness centrality in H-share layer

**Fig. 5.** Time-varying betweenness centrality in A-share and H-share layers.




(a) Dynamic Eigenvector Centrality in A-share layer (b) Dynamic Eigenvector Centrality in H-share layer

**Fig. 6.** Time-varying eigenvector centrality in A-share and H-share layers.

Furthermore, notable shifts in the closeness centrality of cross-listed stocks are observed around two distinct periods—mid-2015 and late 2018—corresponding to the Chinese equity market turbulence and the China–U.S. trade tensions, respectively. These episodes are reflected as vertical bands of warmer colors in the heatmaps,

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indicating a rise in centrality values across a broad set of nodes. The emergence of such patterns suggests that major market shocks can reshape the structure of network, leading certain stocks to temporarily assume more influential positions. During these episodes, firms with high closeness centrality may facilitate the spread of information or shocks. Accordingly, tracking these nodes could offer early warnings of systemic stress.

## 4 Community Detection

The temporal multilayer network analysis reveals that most cross-listed stock pairs exhibit notable differences in their influence across different layers at the same time point, even though they represent the same underlying firm. Therefore, the following section applies community detection techniques to uncover how such influence difference manifest within the network. Community detection is a technique employed to identify structural groupings within a network, revealing closely connected subgroups. In this paper, community detection not only facilitates the analysis of the influence difference of cross-listed firms, but also provides insights into the potential driving factors behind this phenomenon.

### 4.1 Integrated Centrality

To capture the overall importance of cross-listed firms in both markets, this study constructs an integrated centrality measure by leveraging Principal Component Analysis (PCA). Specifically, the analysis draws on four commonly used centrality metrics—degree, closeness, betweenness, and eigenvector centrality—calculated from each layer. Given the potential correlation and redundancy among these indicators, PCA is employed to transform them into a reduced set of uncorrelated components while preserving the dominant patterns in the data. The first two principal components, which jointly account for approximately 92% of the total variance, are retained for further analysis. An integrated centrality indicator is then computed by weighting the component scores using both the eigenvalue contributions and the loadings from the PCA results. This procedure enables us to effectively merge information from multiple dimensions into a single metric that reflects the relative influence of each cross-listed stock within its respective market.

### 4.2 Centrality Imbalance

To quantify how differently a cross-listed firm influences the A-share and H-share markets, we develop a centrality imbalance indicator, calculated as the logarithmic ratio between the integrated centrality scores of its two listings across the respective markets. Then, to capture the temporal characteristics, we compute the centrality imbalance values for each firm across all time-varying multilayer networks and estimate their empirical distributions. Finally, we calculate pairwise Jensen–Shannon divergence between their distributions. This yields a distance matrix that reflects the structural proximity of influence difference among all cross-listed firms.

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### 4.3 Community Detection Results and Analysis

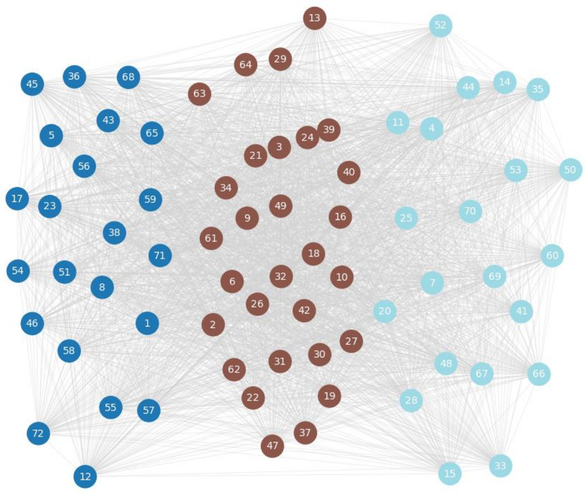
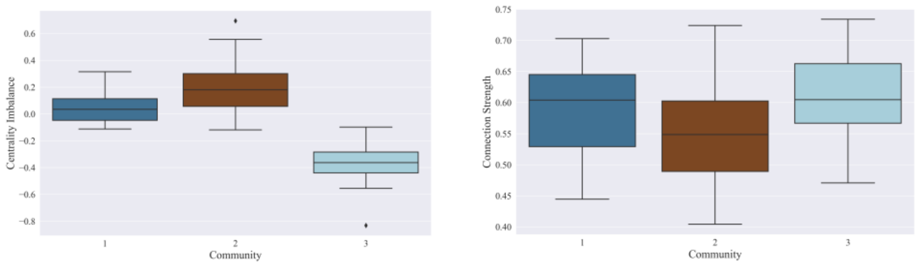



**Fig. 7.** Community structure of cross-listed firms. Each node is colored according to its assigned community: Community 1 (dark blue), Community 2 (brown), and Community 3 (light blue).

Building on the centrality imbalance relationships and the distance matrix, we applied the Louvain algorithm to uncover the community structures within the network of cross-listed firms. This method identifies subgroups in the network by maximizing modularity, thereby revealing underlying community structures [21]. As shown in Fig. 7, the network is divided into three distinct communities, consisting of 22, 29, and 21 firms, respectively. To further examine how cross-listed stock pairs behave within each community, we compare their average centrality imbalance and connection strength.




(a) Centrality Imbalance of A+H stocks across communities

(b) Connection Strength of A+H stocks across communities

**Fig. 8.** Community-level differences among communities.

Firstly, Fig. 8(a) highlights that the centrality imbalance of cross-listed paired stocks are significantly different among the three communities. Specifically, in community 1, the median of the centrality imbalance is close to 0, with relatively low volatility, indicating that the influence difference of these cross-listed firms in the A-share and H-share markets are small. In contrast, in community 2, the centrality imbalance of the

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cross-listed paired stocks are all greater than 0, indicating that these firms have significantly higher influence in the A-share market compared to the H-share market. Conversely, in community 3, the centrality imbalance of the cross-listed firms are all less than 0, with the median around -0.4, suggesting that they are significantly more influential in the H-share market than in the A-share market.

Secondly, as seen in Fig. 8(b), there are notable differences in the connection strength of cross-listed paired stocks, particularly between community 2 and community 3. In community 2, the median connection of paired stocks is below 0.55, whereas in community 3, the connection is tighter, with a median above 0.6. This difference may be related to the maturity of the Hong Kong and Mainland China markets as well as the focus of investors. In the more mature H-share market, there is a higher proportion of international and institutional investors, who are more inclined to focus on large-capitalization and blue-chip firms with stable fundamentals. As a result, they do not pay much attention to cross-listed firms that occupy a relatively important position in the A-share market, thus weakening the connection between paired stocks. On the other hand, investors tend to focus on the price fluctuations of cross-listed stocks in more developed markets [8]. Therefore, for cross-listed firms with greater influence in the H-share market, mainland investors are likely to pay attention to their H-share performance and react accordingly, which strengthens the connection between the paired stocks.

## 5 Conclusion

In this study, we use a multilayer and time-varying network to explore how stocks cross-listed in Hong Kong and Mainland China are connected. By building separate network layers for the A-share and H-share markets and applying a rolling-window method, we find that the links between cross-listed stocks change over time, and become much stronger during major financial events. At the firm level, we create a centrality imbalance index to measure how the influence of paired stocks differs between the two markets. The results show that these differences are common and vary across time. We also use this index to group firms based on community detection, and find that the level of influence difference is closely related to how strongly the two shares of a firm are connected. Overall, this research provides a new way to understand how cross-listed stocks interact across markets and offers useful insights for tracking market risk and improving investment decisions.

In the future, we aim to extend this framework in several directions. First, incorporating additional indicators—such as volatility or tail risk—would allow for the construction of multilayer networks that capture a broader range of connection features. Second, the current model can be further developed into an interconnected multilayer network, enabling the exploration of cross-market information transmission and interlayer dependencies across multiple financial systems. Such extensions could deepen our understanding of systemic risk propagation and enhance the early warning capabilities of network-based financial monitoring systems.

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