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Co-movement forecasting between consumer sentiment and stock price in e-commerce platforms using complex network and entropy optimization

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Stock price and consumer sentiment consistently serve as pivotal economic indicators for the performance and growth of e-commerce enterprises. It is essential to comprehend and forecast the co-movement between the two to inform financing and investment decision-making effectively. Prior research has focused on predicting individual indicators, but not much of them attempt to forecast their co-movement. We propose a novel Rule Combination based on Bivariate Co-movement Network (RC-BCN) approach for bivariate co-movement forecasting. Bivariate co-movement features extracted utilizing the BCN's topological nature instruct the entropy optimization in order to enhance the RC-BCN's predictions. We conduct four sets of experiments on 1,135 data sets from JD.com between 2018 and 2022, where consumer sentiment is measured using text sentiment analysis of online reviews. The results indicate that RC-BCN's prediction accuracy reaches at most 91% under distortion preference and is improved by 18% compared without entropy optimization. This study highlights the value of complex network and entropy theory in forecasting bivariate co-movement for e-commerce enterprises.

KEYWORDS

consumer sentiment, stock price, bivariate co-movement network, entropy optimization, text sentiment analysis

Highlights

- Devising a novel approach called Rule Combination based on Bivariate Co-movement Network (RC-BCN) to solve co-movement prediction problem.
- Predicting the co-movement between Consumer Sentiment (CS) and Stock Price (SP) for e-commerce companies.
- Bi-objective optimization achieved through entropy optimization based on BCN topology.
- RC-BCN outperforms in co-movement between CS and SP forecasting.

- Findings in this study have implications for listed e-commerce companies financing decisions and investor decision-making.

1 Introduction

For publicly listed enterprises, particularly those in the customer-centric retail sector, forecasting the co-movement between Consumer Sentiment (CS) and Stock Price (SP) is crucial for guiding corporate financing decisions and providing valuable insights for investor decision-making. E-commerce enterprises, as typical customer-centric businesses, are significantly influenced by CS in terms of their firm value. Additionally, the e-commerce industry has become a vital component of the global economy. CS and SP are economic signal towers of e-commerce platform performance. Numerous studies have independently examined and forecasted them [1–3]. In contrast, a few studies have integrated these two aspects and established a confirmed correlation between them [4, 5]. These studies have primarily explored the relationship between CS and SP via regression analysis, and employed machine learning to predict SP using CS, thereby enhancing predictive accuracy. Despite these advancements, the dynamic interdependence between CS and SP, particularly regarding co-movement forecasting, has received limited attention in existing literature.

Extant literature indicates that CS impacts SP through multiple pathways. (1) CS can indirectly affect investor behavior through media reports, social media interactions, and other channels, thereby impacting SP [6, 7]. (2) CS reflects the market preferences for a firm's products or services, signaling sales expectations and investor confidence, which in turn affect SP [8, 9]. (3) Some studies suggest that CS can directly and positively influence SP [4, 10]. Positive sentiment boosts market expectations of a firm's future performance, enhancing investor confidence, while negative sentiment undermines market trust, potentially leading to a decline in SP. In addition, related studies have found that: (1) there is a bidirectional causal relationship between sentiment and SP, with potentially positive or negative dynamic [11]. (2) the relationship between CS and SP is complex and nonlinear [5]; and (3) sentiment has a short-term transient effect on SP, suggesting that sentiment changes can serve as early signals of SP movements [11–13].

The relationship between CS and SP is dynamic. However, in contrast to previous studies focusing on the static aspect, this paper examines their dynamic interaction and co-movement forecasting, providing valuable insights into the dynamic relationship between consumer behavior and financial markets. Furthermore, investors can better capture market trends and mitigate potential investment risks by analyzing changes in CS. For customer-centric listed companies, understanding these dynamics enables them to improve financing efficiency and secure greater capital support. Hence, the research question in this study is: how to explore and forecast the co-movement of CS and SP? This research aims to uncover the co-movement's features and forecast them, serving as a reference for corporate financing decisions and investor investment strategies.

Forecasting the co-movement of CS and SP involves obtaining daily CS data and addressing the challenges of nonlinear time series forecasting. Currently, vast quantities of CORs are archived on e-commerce platforms, providing real-time insights into CS.

Moreover, text sentiment analysis is employed to extract the CS from CORs at a finer time scale. Complex network theory has emerged as a powerful tool for analyzing nonlinear time series [14]. Given the dynamic, nonlinear relationship between CS and SP, and the complexity of their interaction patterns, complex network methods are particularly well-suited to uncover and forecast their co-movement. It excels in accurately capturing temporal fluctuations, leading to highly accurate predictions.

In response to the above problems, we propose a novel Rule Combination approach, integrating Bivariate Co-movement Network (RC-BCN) analysis with entropy optimization. It consists of four sequential steps: CS data acquisition, Bivariate Co-movement Network (BCN) construction, feature extraction, and co-movement prediction based on rule combination and entropy optimization. CS data acquisition uses web crawler and text sentiment analysis. We project bivariate time series data into phase space to construct BCN. Particularly, features derived from network topology are used to instruct entropy optimization innovatively. To validate the proposed approach, we conduct four sets of experiments on one dataset. The experiments show that the proposed approach outperforms baseline model.

Our work contributions are summarized as follows:

- Employ complex network to the problem of bivariate co-movement forecasting and develop a novel RC-BCN approach based on entropy optimization for the first time, which performs well.
- Propose a new feature extraction framework, using network topological nature to extract features by projecting bivariate time series into phase space.
- Design a fusion method of combining co-movement features with prediction methods through entropy optimization, which results in high prediction accuracy.

The rest of this paper is organized as follows. [Section 2](#) discusses the related works. [Section 3](#) describes the methodology. [Section 4](#) presents the experiments, and [Section 5](#) discusses the results. [Section 6](#) concludes and outlooks the work.

2 Related works

To address the research question, we conducted a literature review from three aspects. Lastly, we highlighted the extant research gaps and outlined the objectives of our study.

2.1 Evaluating CS through online reviews

CS data can be sourced from two main categories: (1) Authoritative databases, which provide established metrics like the Consumer Confidence Index (CCI), and (2) Evaluating CS through online reviews. Authoritative databases may have limitations in providing real-time, flexible, and fine-grained analysis when supporting detailed research perspectives. Therefore, obtaining CS through CORs have become popular.

Evaluating CS through CORs primarily entails identifying the influencing factors and calculating CS. Various techniques,

such as text regression analysis, machine learning, and the Latent Dirichlet allocation, are employed to ascertain the factors and their respective weights that impact CS, consequently pinpointing the key determinants [15–17]. Additionally, evaluating CS through CORs predominantly utilizes text sentiment analysis methods based on dictionaries, machine learning, and deep learning [18–20]. Among these, the dictionary-based text sentiment analysis method is widely adopted, due to its simplicity. For instance, one approach involves constructing a CS evaluation system by content analysis, followed by the utilization of Probabilistic Linguistic Term sets and improved Analytic Hierarchy Process method to calculate CS based on word frequency statistics [21]. Other approaches include the Center Term Short Sentence Sentiment Orientation, the Probabilistic Linguistic Group Decision-FlowSort, and the Data Envelopment Analysis method to calculate sentiment intensity and dynamically measure CS across multiple dimensions [22–24].

These studies highlight the significance of CORs as a valuable data source for measuring CS, using relatively established evaluation methods. However, it is worth noting that CS in our study refers to consumers' overall sentiment on shopping platforms. While influenced by multiple factors, CS cannot be directly quantified as the sum of sentiment values derived from these individual factors. Hence, in quantifying CORs, we adopt a dictionary-based algorithm that matches overall CS vocabulary to measure the sentiment intensity of CORs. This approach effectively captures overall CS.

2.2 Bivariate co-movement features

Co-movement analysis between CS and SP typically focuses on their correlation, particularly in predicting SP volatility utilizing CS. However, limited research has been conducted on the co-movement features between CS and SP, while an extensive body of literature exists on bivariate co-movement features, showcasing more mature methodologies. The research subjects include inter-country currency exchange rates, the intersection of artificial intelligence and energy sectors, as well as the relationship between dirty and clean energy [25–27]. These research covers both static co-movement features, such as bivariate interdependence and quantile co-movement, and dynamic features, including co-movement structure and fluctuations. Although studies on CS and SP co-movement are typically classified as static, their co-movement is inherently dynamic.

Common methods for analyzing dynamic co-movement features include wavelet analysis, DCC-GARCH model, the Thick Pen method, Temporal Convolutional Network (TCN), and complex network analysis [25, 28–31]. Among these, wavelet analysis has high sensitivity to the selected wavelet basis function and scale parameters. The DCC-GARCH model generally assumes that the data are normally distributed. The Thick Pen method tends to be subjective in parameter setting. TCN depends on the quality of input data and is sensitive to the hyperparameter. In contrast, the co-movement between CS and SP does not necessarily conform to the normal distribution. Complex network analysis provides an objective means to visualize nonlinear and nonintuitive relationships between bivariate.

Scholars have employed symbolic dynamics methods to map time series data into BCN, and have utilized network indicators

to analyze bivariate dynamic co-movement features. This approach is grounded on coarse-graining partitions of phase space, involves constructing coarse-grained rules to transform time series into symbols, defining symbol sequence vectors as nodes, establishing a network resulting from the transition frequency of the symbol sequence vectors in the time series [14]. The co-movement features are mainly extracted by using network topology indicators such as node strength, node centrality, weighted cluster coefficient and community detection [32, 33]. Despite employing various network indicators in prior research, there remains a gap in the literature regarding a comprehensive analytical framework for identifying bivariate co-movement features and guiding the development of a bivariate co-movement prediction model.

2.3 Bivariate co-movement prediction

The research area of bivariate co-movement forecasting includes different stock prices, the multi-step network traffic states, innovative and traditional financial assets in different regions [34–36]. Research topics in co-movement forecasting focus on the future trends of bivariate co-movement, including correlations between stock prices [34], crude oil prices volatility [37], and volatility spillovers across economic sectors [38]. Given the high volatility of both CS and SP, this study aims to forecast the co-movement trend between CS and SP, consistent with prior research.

In the absence of distinct regularities, nonlinear systems commonly adopt integrated forecasting models, incorporating techniques such as data mining, cross entropy, Convolutional Neural Network-Long Short Term Memory (CNN-LSTM), Back Propagation (BP) Neural Networks, and link prediction methods, to improve predictive accuracy [39–42]. The aforementioned methods, particularly machine learning techniques, have demonstrated significant efficacy in predicting bivariate co-movement by optimizing model hyperparameters. However, these methods face challenges in explaining the underlying mechanisms driving the observed results. In contrast, the complex network approach not only uncovers the co-movement characteristics of bivariate relationships but also effectively predicts their dynamics, eliminating the need for resource-intensive and time-consuming experimental processes.

Time series forecasting algorithms based on complex network have shown significant advancements in recent years. These methods, such as maximum node weight and maximum visibility forecasting have been developed based on the principles of complex network link prediction [43, 44]. The current widely used link prediction algorithms are often based on various node similarities, including local similarity, weighted similarity and random walk similarity [45–47]. Typically, the greater the similarity between two nodes in the network, the higher the likelihood of connectivity between them. While numerous algorithms exist for bivariate co-movement prediction, each validated in different fields, it is worth mentioning that the co-movement features within a network can vary significantly across different time series networks. As a result, predictions made by a single forecasting method may exhibit biases when compared to actual outcomes.

2.4 Research gap and objectives

Bivariate co-movement forecasting has been studied on mostly macroeconomic indicators. Limited by the availability of data, previous studies have less often landed on firm-level economic indicators, especially on the co-movement of CS and SP. For e-commerce companies, the abundance of CORs on e-commerce platforms provides valuable opportunities for in-depth analysis. Previous studies have developed various methods to extract co-movement features and demonstrated promising results in bivariate co-movement prediction. However, challenges persist in systematically extracting these features, applying them for prediction, and interpreting results, particularly in nonlinear systems. These gaps underscore the necessity of exploring novel approaches to predict the co-movement between CS and SP in the context of e-commerce enterprises.

Addressing the gaps identified in the extant literature, this study introduces a novel approach, grounded in complex network theory, to forecast the co-movement dynamics between CS and SP of e-commerce platforms. The basic approach is: design an algorithm for collecting and quantifying CORs on e-commerce platforms to obtain a more finely-grained CS; and then transform the time series data of CS and SP into BCN and extract the co-movement features based on the network's topology; construct a rule combinations model based on the co-movement features to forecast future co-movement mode. Moreover, model optimization involves entropy optimization guided by co-movement features.

3 Research methodology

3.1 Time-series data collection

The closing price is a crucial indicator that reflects daily market trends and is easily accessible through stock trading platforms. The process of obtaining the CS involved four key steps (see Figure 1). Firstly, CORs are collected using web crawling techniques. Secondly, a dictionary-based text sentiment analysis method is applied, utilizing the Jieba text segmentation tool to segment, analyze, and match the text with the dictionary for initial data processing. Then, sentiment values are calculated based on the part-of-speech and weights assigned by the dictionary. Finally, the obtained sentiment values that passed the test are used as the CS. The test algorithm demonstrated an accuracy of 84.77% when applied to the Tan Songbo hotel review corpus, confirming its practical applicability.

Since reviews consist of sentences, Equation 1 calculates sentiment scores at the sentence level, while Equation 2 aggregates them to determine the review-level sentiment score, and Equation 3 standardizes it.

$$\text{Sentence's score} = (P - N_p) \times W \times (-1)^{\text{Neg}} \quad (1)$$

where P represents the number of active words, N_p refers to the number of passive words, and Neg denotes the count of negation words (such as “not,” “no,” and other similar terms). The sentiment score for each sentence is adjusted by multiplying it by $(-1)^{\text{Neg}}$, reflecting the principle that double negation leads to

affirmation [48]. W is the weights corresponding to adverbs of degree. If there are no adverbs of degree, the weight is considered as 1. Generally, a sub-sentence contains only one adverb of degree. If there are multiple adverbs of degree, the weight corresponding to the first matched adverb is used.

$$\text{Review's score} = \sum \text{Sentence's score} \quad (2)$$

$$\text{CS} = \frac{\text{Review's score} - \text{Review's score}_{\min}}{\text{Review's score}_{\max} - \text{Review's score}_{\min}} \times 100 \quad (3)$$

where CS is represented as a numerical value quantified on a scale from 0 to 100, derived from text sentiment analysis.

3.2 BCN construction

3.2.1 Node determination

In this study, co-movement describes the relationship between CS and SP, while the co-movement symbol represents both the direction and magnitude of their interaction. The coarse graining method in symbol dynamics and time series involves defining the co-movement sequence as Lp_i , which represents the product of ΔCS (the first-order difference of CS) and ΔSP (the first-order difference of SP) [49]. Avg+ signifies the average of $\Delta\text{CS} \times \Delta\text{SP}$ when their product is positive, while Avg- denotes the average of the product is negative. Subsequently, Lp_i is subdivided into the following five cases, as shown in Equation 4.

$$Lp_i = \begin{cases} Y, \Delta\text{CS} \times \Delta\text{SP} \geq \text{Avg+} & \text{Violent co-movement in the same direction} \\ y, 0 < \Delta\text{CS} \times \Delta\text{SP} < \text{Avg+} & \text{Slight co-movement in the same direction} \\ o, \Delta\text{CS} \times \Delta\text{SP} = 0 & \text{No co-movement} \\ n, \text{Avg-} < \Delta\text{CS} \times \Delta\text{SP} < 0 & \text{Slight co-movement in opposite directions} \\ N, \Delta\text{CS} \times \Delta\text{SP} \leq \text{Avg-} & \text{Violent co-movement in opposite directions} \end{cases} \quad (4)$$

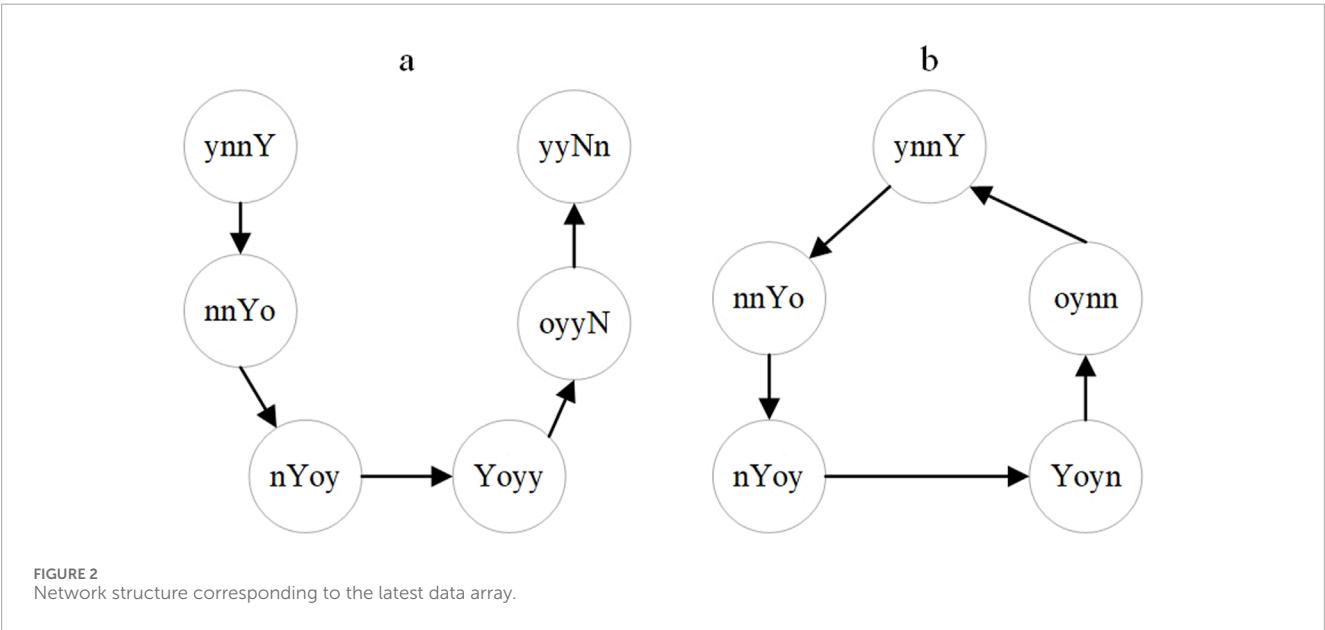
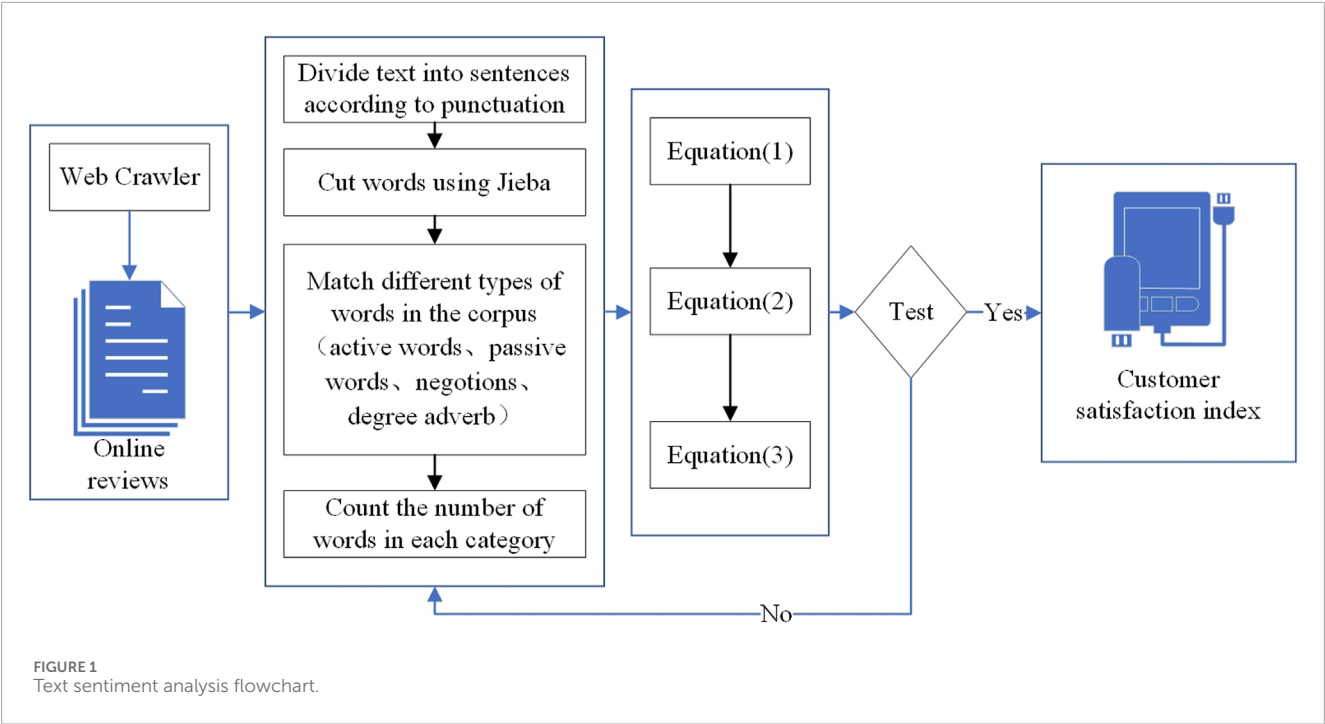
Thus, the co-movement between CS and SP can be represented by a continuous symbol sequence, and the corresponding symbol sequence is given in Equation 5.

$$Lp_i = (Lp_1, Lp_2, \dots, Lp_w) (Lp_i \in (Y, y, o, n, N), w = 4) \quad (5)$$

Given that stock trading typically spans five consecutive days, with statutory holidays excluded from consideration, we define a node as the co-movement of four consecutive days. $w = 4$ ensures the balance of the time window, though its value can be adjusted based on the sample size in this study. The symbol sequence Lp_i serves as the data sliding window with a step size of 1, and the coarse-grained symbol sequence is converted into partially overlapping symbol intervals, each representing different co-movement modes.

3.2.2 Determination of edges and weights

Using the coarsened data, edges in the co-movement network are established by connecting the previous co-movement mode combination to the neighboring subsequent co-movement mode combination. The number of transitions between two combinations of the same mode function as the edge weight. Therefore, a weighted directed BCN is constructed to depict the co-movement modes between CS and SP.



If the symbol sequence mapped for the time series is {ynnYoyyNn}, the corresponding latest node is {yyNn}. Figure 2A illustrates the network structure, where the number of nodes equals the count of co-movement modes. However, if the symbol sequence mapped for the time series is {ynnYoyynnY}, and the latest node is {ynnY}, the number of nodes is less than the count of co-movement modes, as depicted in Figure 2B. In practical network construction, when the sample size is sufficient, it often resembles the structure shown in Figure 2B. If the sample size is limited, one can reduce the use of symbols or symbol combinations (i.e., reduce w) to construct the BCN.

3.3 Feature extraction

We derive BCN's features across four key dimensions to guide the subsequent predictions, with the specific features and indicators detailed in Table 1.

3.4 Co-movement prediction model

Co-movement forecasting is the prediction of the next day's CS and SP co-movement symbol. For instance, if we observe a co-movement mode on day t , denoted as {ynn y }, forecasting the

TABLE 1 Outlines the framework of the feature extraction model for BCN.

Dimension	Indicators	Formulas
Influence	Node strength	$S_{i_out} = \sum_{j \in N_i} W_{ij}, S_{i_in} = \sum_{j \in N_i} W_{ji}, S_i = S_{i_out} + S_{i_in}$ [49] where S_i is node strength of node i , N_i is the set of neighbors of node i , and W_{ij} is the weight of node i to node j
	Strength distribution	$P(s) = \frac{S_i}{\sum_{i=1}^N S_i}$ where N is the total number of nodes, $P(s)$ is strength distribution
Clustering	Clustering coefficient	$C_i = \frac{E_i}{k_i(k_i-1)}$ [49] where C_i is the clustering coefficient of node i , k_i is the degree of node i , and E_i is the number of actual edges between the neighboring nodes of node i
	Weighted Clustering coefficient	$C_{i_weighted} = \frac{1}{S_i(k_i-1)} \sum_{(j,k)} \frac{w_{ij}+w_{ik}}{2} a_{ij}a_{ik}a_{jk}$ where a_{ij} indicates whether there is a link between node i and node j : 1 if a link exists, and 0 otherwise
Periodicity	Betweenness centrality	$W_k = \sum_{(i,j)} \frac{C_k(i,j)}{C(i,j)}$ [15] where W_k is the betweenness centrality of node k . $C(i,j)$ is the total number of all shortest paths between node i and node j . $C_k(i,j)$ is the number of paths through node k
	Average path length	$L_{avg} = \frac{1}{N(N-1)} \sum_{i \neq j} d_{ij}$ [15] where d_{ij} is the number of edges in the shortest path between nodes i and j
Orderliness	Standards Network Strength Entropy	$G = \frac{-\sum_{s=1}^N P(s) \ln P(s)}{\ln N}, G_{i_in} = \frac{-P(s)_{ij} \ln P(s)_{ij}}{\ln n_{i_in}}, G_{i_out} = \frac{-P(s)_{ij} \ln P(s)_{ij}}{\ln n_{i_out}}$ [58] where G presents the standards network strength entropy. G_{i_in} and G_{i_out} are the standards strength in-entropy and out-entropy of node i . n_{i_in} is the number of nodes entering node i . n_{i_out} is the number of nodes that node i points to. $P(s)_{ij} = \frac{w_{ij}}{\sum_{j=1}^N w_{ji_in}}, P(s)_{ij} = \frac{w_{ij}}{\sum_{j=1}^N S_{ij}}$

TABLE 2 Node strength and strength distribution of each co-movement mode.

No.	Node	S	Ratio (%)	No.	Node	S	Ratio (%)
1	nnnn	98	4.34	11	nyyy	68	3.01
2	nnny	80	3.54	12	ynny	67	2.96
3	ynyn	78	3.45	13	nnyy	66	2.92
4	yynn	78	3.45	14	nnyn	66	2.92
5	nyny	78	3.45	15	yyyn	62	2.74
6	yyyy	76	3.36	16	nynn	62	2.74
7	ynyY	74	3.27	17	yyYy	14	0.62
8	yYny	70	3.10	18	yYyn	14	0.62
9	yynn	70	3.10	...	...	...	...
10	nyyn	70	3.10	268	YYny	1	0.04

mode for day $t + 1$ relates to predicting the mode $\{nny\}$. Prior studies have indicated that the total occurrence time of different co-movement modes follows an approximately linear distribution [49]. This implies that with sufficient data, new co-movement modes will not arise in the short term. Hence, we utilize mode transformation relationships for forecasting.

3.4.1 BCN optimization based on entropy principal

To ensure the accuracy of predictions, it is essential to adjust the network structure to enhance its clarity, particularly in

cases where chaotic nonlinear systems exhibit strong randomness. Therefore, the partial edge weights are adjusted to improve its predictability based on entropy optimization. Entropy optimization is a method for finding the optimal solution under given constraints by maximizing or minimizing an entropy-based objective function, leveraging the mathematical properties of entropy and principles of information theory [50]. Entropy, as an optimization and correction tool, is used to optimize the return statistics that do not follow Gaussian distribution, and to correct the geometric Brownian motion model by relaxing the assumption of lognormal distribution [51, 52]. Furthermore, entropy optimization is utilized in identifying topological changes in complex networks, assessing network consistency, and reducing knowledge distillation loss in deep neural networks by adjusting network entropy [53–55]. The use of entropy is prevalent in economics, with applications ranging from risk measurement and portfolio optimization to the design of combined economic emission dispatch optimization algorithms, all of which contribute to enhancing the scientific basis for decision-making [51, 56, 57]. The aforementioned studies demonstrate the broad applicability and notable effectiveness of entropy optimization across various economic domains.

The standard network strength entropy is employed as a measurement tool, which extends Shannon entropy to quantify the uncertainty in the distribution of node or edge strength [58]. This measure is standardized to enhance its applicability to network analysis. Building upon this, the approach constructs a bi-objective entropy optimization model that aims to minimize network distortion and simultaneously adjusts the weights of selected edges to reduce the network's output entropy (see G_1), thereby achieving overall network optimization. Minimizing network distortion ensures that the adjustment of edge weights has minimal impact on the network's topological structure, which is mathematically represented by G_2 . The selected edges set refers to the edges connected to nodes with higher recognizability, which

are typically associated with lower entropy values. These edges are crucial for reducing network out-entropy while preserving the network's essential features. Based on these objectives, the following model is proposed (see Equation 6):

$$\begin{aligned} G_1 &= \min_x \left\{ \frac{\sum_i^N G_{i_{out}}}{N} \right\} \\ G_2 &= \min_x \left\{ \frac{\sum_{i=1}^N \Delta S_i}{N} + \frac{\sum_{i=1}^N \Delta C_{i_{weighted}}}{N} \right\} \end{aligned} \quad (6)$$

Where x represents the adjustment applied to the weight of the edge.

3.4.2 RC-BCN model

In the process of constructing a BCN, it is crucial to consider two scenarios for the latest nodes:

- (1) If the latest node $V_i^{(t)}$ has no out-neighbor node in BCN (see Figure 2A), then the future node that appears at $t+1$ can be estimated according to the trend extrapolation method [59]. That is, if $V_i^{(t)} = \{yyny\}$, then $V_{i \rightarrow j}^{(t+1)} = \{ynyy\}$. In fact, this situation can be avoided when building the BCN.
- (2) If $V_i^{(t)}$ has out-neighbor nodes in BCN (see Figure 2B), the set of out-neighbor nodes is defined by Equation 7.

$$V_{i \rightarrow j}^{(t+1)} = \{V_{i \rightarrow j_1}^{(t+1)}, V_{i \rightarrow j_2}^{(t+1)}, \dots, V_{i \rightarrow j_n}^{(t+1)}\}, j_1, j_2, \dots, j_n \in [1, N] \quad (7)$$

Based on the preceding analysis (3.2.2), the future nodes at $t+1$ are one of the elements in $V_{i \rightarrow j}^{(t+1)}$. There are three common rules to determine the exact nodes.

Rule 1: The principle of the greatest Node Similarity. Link prediction techniques are applied, where the probability of a potential connectivity between nodes is determined by computing the similarity between two nodes. The node with the highest similarity is selected as the predicted node, and in case of tie, preference is given to the relatively most recent node.

Given a pair of nodes (v_i, v_j) , the rules for calculating the node similarity are as follows: If the BCN exhibits significant clustering, a local feature-based similarity formula is applied (see Equation 8); otherwise, a global-based similarity formula is utilized (see Equation 9) [42].

$$S_{ij}^{JC} = \frac{|\Gamma(i) \cap \Gamma(j)|}{|\Gamma(i) \cup \Gamma(j)|} \quad (8)$$

where $\Gamma(i)$ and $\Gamma(j)$ are the sets of out-neighbor nodes of v_i and v_j respectively.

$$S_{ij}^{WJC} = \frac{\sum_{x \in \Gamma(i) \cap \Gamma(j)} (w_{ix} + w_{xj})}{\sum_{x \in \Gamma(i) \cup \Gamma(j)} (w_{ix} + w_{xj})} \quad (9)$$

where w_{ix} , w_{xj} , w_{iy} and w_{yj} are edge weights, respectively. This formula takes into account the weight of the edge on the basis of Equation 8.

If the maximum value of either S_{ij}^{JC} or S_{ij}^{WJC} is 0, it is not possible to predict future nodes. In this case, Rule 2 or Rule 3 are employed for combined prediction.

Rule 2: The principle of the greatest node strength, that is, select the node with the largest node strength from $V_{i \rightarrow j}^{(t+1)}$. In case of tie, the relatively most recent node is selected.

Rule 3: The principle of the greatest connection strength, that is, select the node with the largest connection strength from $V_{i \rightarrow j}^{(t+1)}$. In the event of a draw, the relatively most recent node is selected.

Following these rules, co-movement modes prediction function was established, as shown in Equation 10.

$$\hat{V}_{i \rightarrow j}^{(t+1)} = f(V_i^{(t)}) + \xi_t, t \in [0, I] \quad (10)$$

where $f(x)$ is the composite function comprising six co-movement prediction models: M-1 (Trend extrapolation method and Rule 1-Equation 8 and Rule 2), M-2 (Trend extrapolation method and Rule 1-Equation 8 and Rule 3), M-3 (Trend extrapolation method and Rule 1-Equation 9 and Rule 2), M-4 (Trend extrapolation method and Rule 1-Equation 9 and Rule 3), M-5 (Trend extrapolation method and Rule 2), and M-6 (Trend extrapolation method and Rule 3). ξ_t is the error.

3.4.3 Evaluation of model prediction accuracy

The co-movement prediction of CS and SP refers to forecasting both the direction and strength of their co-movement. Hence, model prediction accuracy is assessed in terms of two aspects: accurately predicting both the co-movement direction and strength, or solely the co-movement direction. The evaluation indicators for accurately predicting both co-movement direction and strength are defined in Equations 11, 12.

$$D_1 = \frac{1}{L} \sum_{t=1}^L a_t \quad (11)$$

$$a_t = \begin{cases} 1, & V_{i \rightarrow j}^{(t+1)} = \hat{V}_{i \rightarrow j}^{(t+1)} \\ 0, & V_{i \rightarrow j}^{(t+1)} \neq \hat{V}_{i \rightarrow j}^{(t+1)} \end{cases} \quad (12)$$

The evaluation indicators for accurately predicting the co-movement direction are given in Equations 13, 14.

$$D_2 = \frac{1}{L} \sum_{t=1}^L b_t \quad (13)$$

$$b_t = \begin{cases} 1, & V_{i \rightarrow j}^{(t+1)} \cong \hat{V}_{i \rightarrow j}^{(t+1)} \\ 0, & V_{i \rightarrow j}^{(t+1)} \neq \hat{V}_{i \rightarrow j}^{(t+1)} \end{cases} \quad (14)$$

$V_{i \rightarrow j}^{(t+1)} \cong \hat{V}_{i \rightarrow j}^{(t+1)}$ signifies the predicted and actual symbols have matching directions.

4 Experiments

4.1 Data preparation

A set of experiments was conducted using JD.com, a prominent B2C online shopping platform. According to a 2022 Tencent report, electronic products on JD.com accounted for over 60%. Hence, 44 high-selling electronic products were selected from JD.com's main

product categories, encompassing five renowned brands: Huawei, Apple, Samsung, Xiaomi, and OPPO.

A total of 92,722 CORs were collected, spanning from 9 January 2018, to 15 August 2022. The collected CORs include the consumers' review and the date. Textual sentiment analysis resulted in a 1,645-day CS dataset. Given that multiple data points exist for the same day, we use the daily average to more accurately reflect the overall CS for that day. The closing price from 9 January 2018, to 15 August 2022, was obtained from the Straight Flush website.

After data merging, 1,135 sets of data were obtained. Subsequently, a Spearman correlation coefficient test was conducted, revealing a significant positive correlation between them. The summary statistics indicate that the data do not follow a normal distribution (see [Supplementary Appendix A](#)). This suggests that the relationship between the variables is complex and warrants further analysis using nonlinear methods. To further process the data, coarse-graining and sliding window techniques were employed, resulting in the generation of 268 nodes and 1,134 edges.

4.2 CS and SP co-movement network construction

[Figure 3](#) displays the CS and SP Co-movement Network (CS-SPCN). It shows obvious differences in the influence of the co-movement modes, and the clustering between different modes.

Furthermore, as the data volume expands, the increase in node count exhibits a diminishing trend (see [Figure 4](#)). The temporal intervals between the occurrence of new co-movement modes and those of old modes eventually grow longer (see [Figure 5](#)). This implies that future modes are likely to be once-emerged modes. It also demonstrates that JD.com's CS-SPCN adheres to the application premise of the co-movement mode prediction model developed in this study.

4.3 Feature extraction

4.3.1 Influence

- (1) The co-movement between CS and SP is primarily slightly negative. Specifically, there were 98 instances of opposite-direction co-movement over four consecutive days, while only 76 instances of same-direction co-movement occurred (see [Table 2](#)). This reflects the risk of reverse reactions and potential misalignment between CS and SP.
- (2) The CS-SPCN exhibits an uneven distribution, characterized by significant disparities in nodes and edges. The initial 16 nodes demonstrate substantial node strength, accounting for a cumulative strength distribution of 51.46%. In contrast, there are 113 nodes with a node strength of two or less, representing only 9.96% of the total strength (see [Figure 6A](#)). [Figure 6B](#) demonstrates that the cumulative strength distribution approximately follows a power-law distribution, indicating that the CS-SPCN is a scale-free network. There are primarily 16 manifestations of co-movement modes. These 16 co-movement modes frequently transition to other modes, or vice versa, demonstrating a high frequency of shifts between

modes. This suggests that market reactions are nonlinear and complex, and companies must focus on the most influential factors, concentrating their resources on understanding core sentiment and market responses.

4.3.2 Clustering

The CS-SPCN exhibits a certain degree of clustering, with some nodes having strong connections, forming small and tightly-knit communities or subgroups. There are 29 nodes with a non-zero clustering coefficient. Both {yyyy} and {nnnn} have greater clustering coefficients and strength (see [Figure 7](#)). The highest clustering coefficient value observed is 0.5, suggesting a generally modest level of network cluster. Additionally, the weighted clustering coefficients of the nodes {nnnn}, {Ynnn} and {ynnn} exceed 0. This suggests that co-movements are interrelated, and companies should consider the interactions of multiple co-movements, rather than focusing on a single direction, in decision-making.

4.3.3 Periodicity

- (1) Nodes with violent co-movement symbols exert substantial network influence. In terms of transition capabilities, {ynny, nnyY, Nynn, YyYN, YYyY} are the main transformation hubs. Businesses and investors should proactively identify market signals and focus on key moments to leverage critical decision-making opportunities. [Figure 8A](#) indicates a relatively even distribution of node betweenness centrality. [Figure 8B](#) shows that the top 26 nodes have a 25% share of cumulative betweenness centrality, indicating that 9.7% of the nodes perform 25% of the transit function. Some nodes with low strength play essential hub roles, as evidenced by the circled points in [Figure 8C](#).
- (2) The co-movement between CS and SP exhibits a cyclical pattern, with a periodicity of 8 days. The CS-SPCN demonstrates an average path length of 7.696. Given a mode generation sliding unit of 1 day, transitions between modes span approximately 8 days, thus accentuating the periodic feature of the co-movement. Companies should develop forecasting models to adjust decisions promptly in response to market cycles.

4.3.4 Orderliness

Overall, the network exhibits a high degree of randomness and disorder, as evidenced by the standard network strength of the BCN exceeding 0.8, which suggests that predicting the next node in the network without relying on local information is highly challenging. This also indicates that businesses operate in a highly uncertain environment, where both businesses and investors face the risk of being unable to accurately predict future market changes, thereby impacting the effectiveness and precision of their decisions. This study addresses the challenge of predicting the nodes at $t+1$ based on the nodes at t . Networks with lower out-entropy demonstrate higher predictability, as reduced out-entropy reflects less uncertainty in the outgoing connections of nodes. Analyzing the local characteristics reveals that the average in-entropy and out-entropy of each node follow specific patterns. Particularly, nodes set with violent co-movement at the end state, exhibit the lowest average in-entropy and out-entropy (see [Table 3](#)). As a result,



To enhance the network's predictability, the edge weight of the node set with violent co-movement at the terminal state is adjusted to x . To minimize network distortion and effectively reduce network out-entropy, the value of x is constrained within the range [2,7.696]. To accurately obtain the Pareto frontier in a bi-objective optimization problem, the Eel and Grouper Optimizer (EGO) algorithm is employed. EGO is a novel meta-heuristic algorithm inspired by the symbiotic interactions and foraging strategies of eels and groupers in Marine ecosystems [60]. The algorithm's flexible transition between the exploration and development phases, along with its population-based nature, effectively reduces the risk of converging to local optima. The Pareto frontier is calculated using

Given that $4 < G_2 < 6$, the decision-maker shows a preference for network distortion. For $2 < G_2 < 4$, distortion neutrality is observed. If $0 < G_2 < 2$, the decision-maker demonstrates aversion to distortion. Three optimal solutions are selected from these three acceptable regions for subsequent prediction.

Sample of model estimation. The growth of a business usually follows an “S” curve. In addition, the network structure exhibits

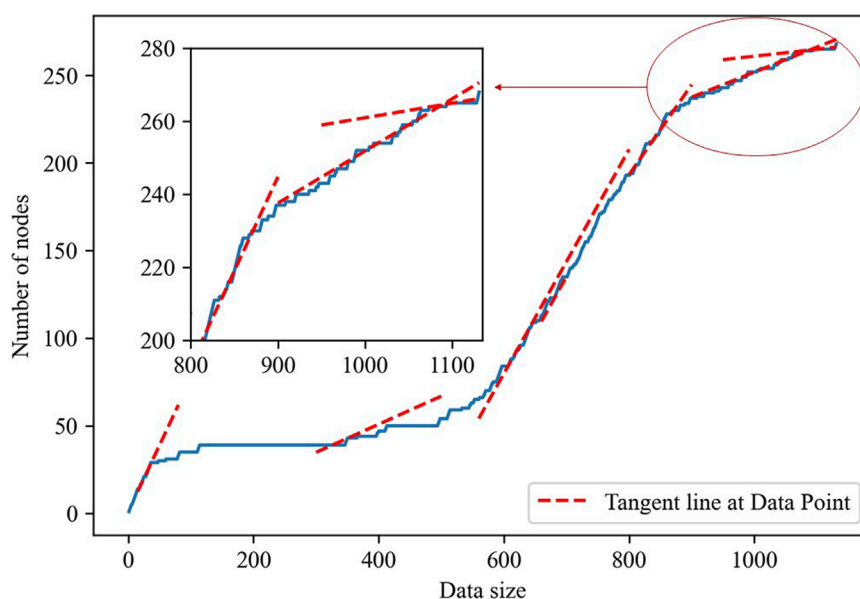


FIGURE 4
Relationship between Data Size and Number of Nodes.

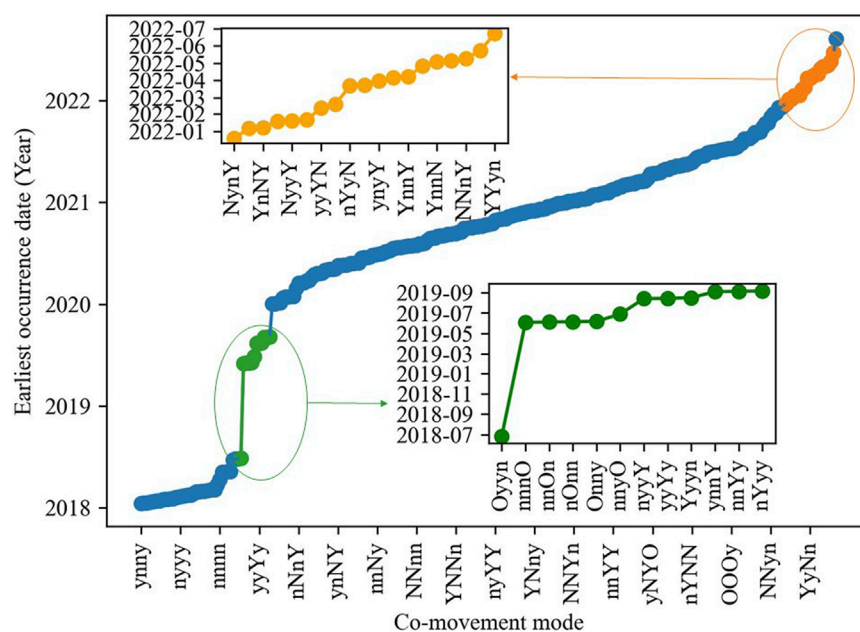


FIGURE 5
Relationship between Co-movement Modes and Earliest Occurrence Times.

annual instability in the post-pandemic period. By utilizing up-to-date data, more precise predictions can be generated. Hence, a sample of co-movement modes from 2022 is employed to evaluate the accuracy of the model.

Implementation details. To assess the effectiveness of BCN optimization, we conducted four experimental sets with varying distortion preferences and baseline model, comparing the prediction accuracy of each model. Experiment A0 serves as the baseline model,

where the BCN is not optimized. Experiment A1 represents the predictive model under distortion aversion ($x = 2.21$), Experiment A2 corresponds to distortion neutrality ($x = 4.36$), and Experiment A3 reflects a distortion preference ($x = 6.31$). These experiments were designed to investigate the impact of varying distortion attitudes on predictive accuracy, thereby validating the effectiveness of BCN optimization. Furthermore, given the limited frequency distribution of violent co-movements, the analysis focuses solely on

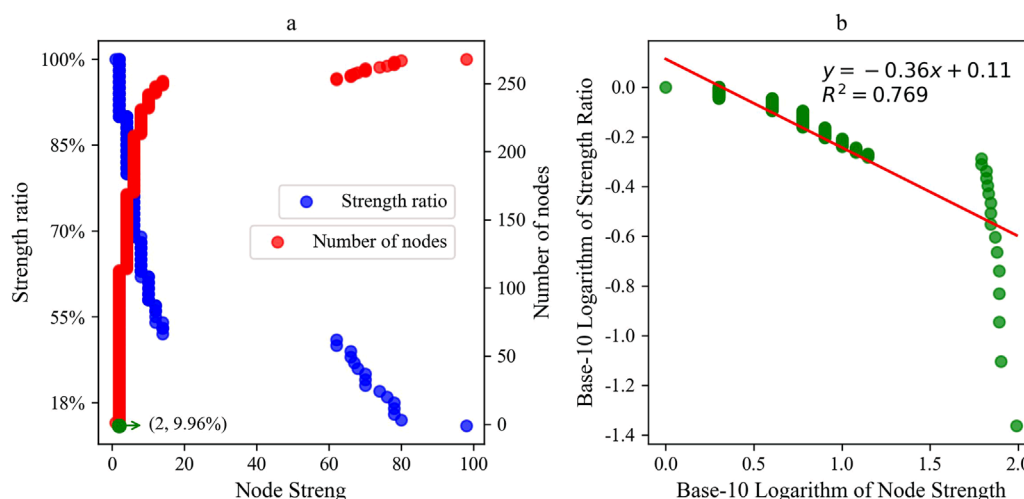


FIGURE 6
Relationship of Node Strength with Strength Ratio and Number of Nodes. Strength Ratio represents the ratio of the cumulative strength of the nodes to the sum of all nodes' strength.

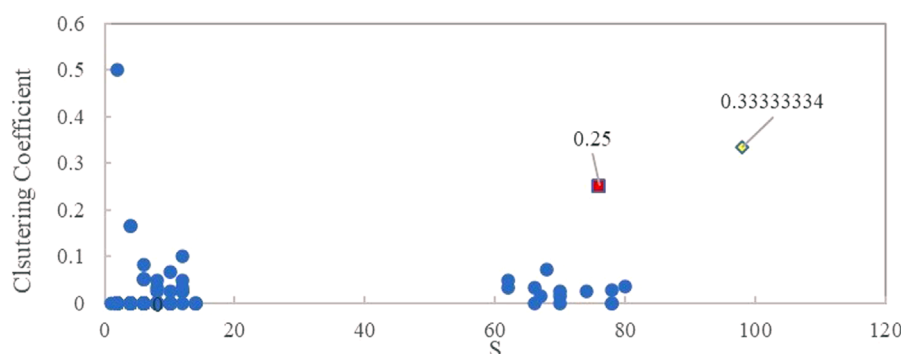


FIGURE 7
Relationship between Node Strength and Clustering Coefficient.

forecasting the direction of co-movement rather than its degree. The accuracy of the prediction model is evaluated using D_2 . We randomly selected 200 samples from the dataset and calculated the accuracy of the prediction results.

Figure 10A0 shows that M-5 and M-6 demonstrate higher prediction accuracy compared to other models, suggesting that node strength and edge weight are the primary factors influencing the co-movement between CS and SP, while the influence of node similarity appears to be negligible. By comparing with Figure 10A0, it is evident that the prediction accuracy of M-5 and M-6 is significantly improved by entropy optimization, whereas the impact on the prediction accuracy of M-1 to M-4 is less pronounced. This is primarily because the optimization of the network has a direct and significant impact on the strength of nodes and edges, but does not significantly affect the similarity between nodes. Furthermore, as the forecasting length (FL) increases, the prediction accuracy tends to converge around 50%–60%. The prediction accuracy of M-6 is nearly identical under the conditions of distortion aversion and neutrality, with both exceeding 80% (see Figures 10A1, A2). The prediction

accuracy of M-5 and M-6 can approach 90% under the distortion preference condition (see Figure 10A3).

Compared to RC-BCN alone, the prediction accuracy of our proposed RC-BCN based on entropy optimization is, on average, improved by 15.5% under M-6. To further elucidate the contribution of this study, we compare the method proposed herein with the prediction results obtained from the BP neural network and LSTM models. For the problems addressed in this paper, both the BP neural network and LSTM models use the autoregressive method to predict the values of CS and SP, respectively. The co-movement direction of CS and SP is then calculated based on the prediction results, with the methods denoted as BP₁ and LSTM₁. Furthermore, the direction of co-movement can be directly classified and predicted, denoted as BP₂ and LSTM₂. The parameter settings for the four models are presented in Table 4 and Figure 11 illustrates that M-5 and M-6 outperform both BP and LSTM in terms of prediction accuracy.

We employ M-5 and M-6 to predict the next 4 days co-movement modes under the different preferences of decision makers. The latest co-movement mode is {YYny}, originating from

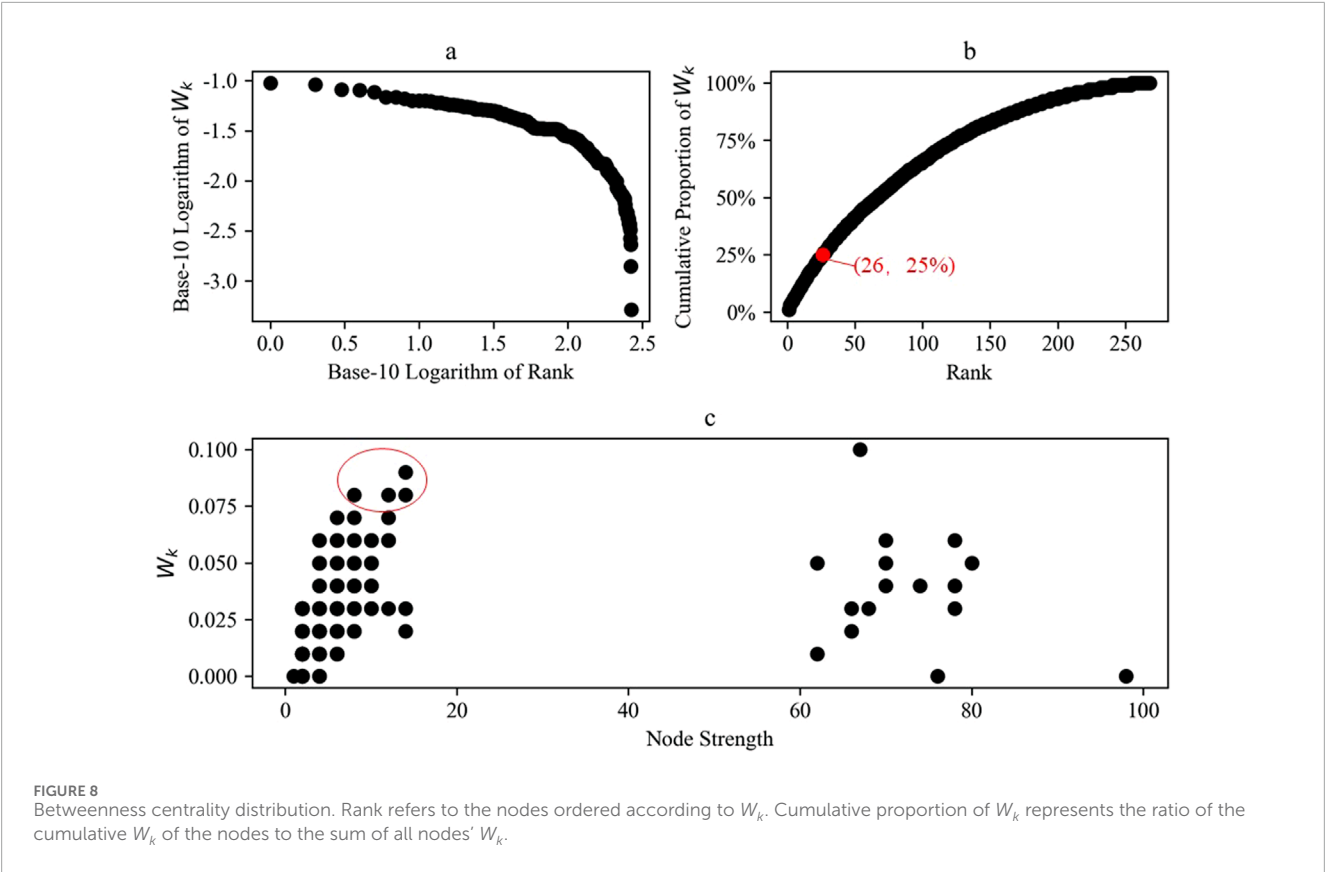


TABLE 3 Network entropy.

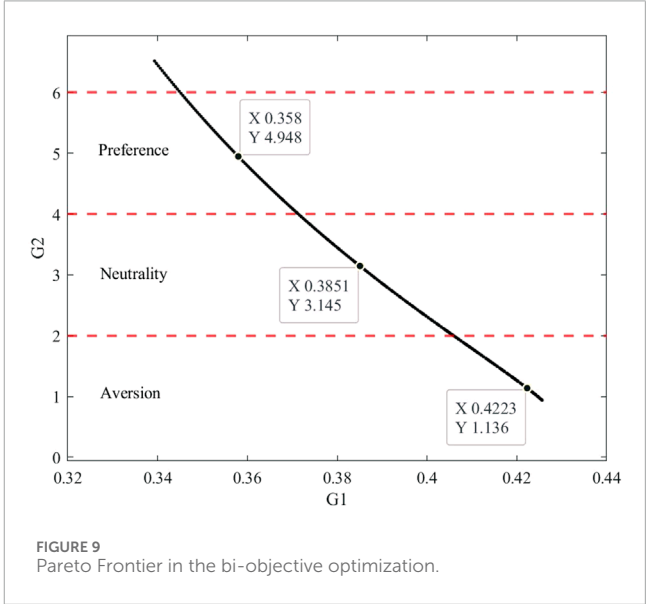
Items	A	B	A + B
Total in-entropy	55.46	71.97	127.43
Average in-entropy	0.45	0.50	0.48
Percentage of Nodes with In-Entropy = 0	53.23%	45.14%	48.88%
Total out-entropy	54.46	71.30	125.77
Average out-entropy	0.44	0.50	0.47
Percentage of Nodes with Out-Entropy = 0	54.84%	45.14%	49.63%
Number of nodes	124	144	268

^aA node set exhibiting violent co-movement at its terminal state; B A node set exhibiting slight co-movement at its terminal state.

15 August 2022. The co-movement modes for the last 4 days are {Ynyy,nyyy,yyyy,yyyn} across different scenarios.

5 Discussion

The co-movement forecast between CP and SP could assist publicly listed e-commerce companies in financing decisions and investors in making investment decisions. Motivated by it, we



explore the forecast approach of the co-movement modes between the two based on complex network and entropy optimization. Specially we project the time series data into the phase space, and enhance the prediction through rule combination and entropy optimization instructed by features extracted from network topology indicators. We conducted four experimental sets, with results indicating the model's successful predictive performance.

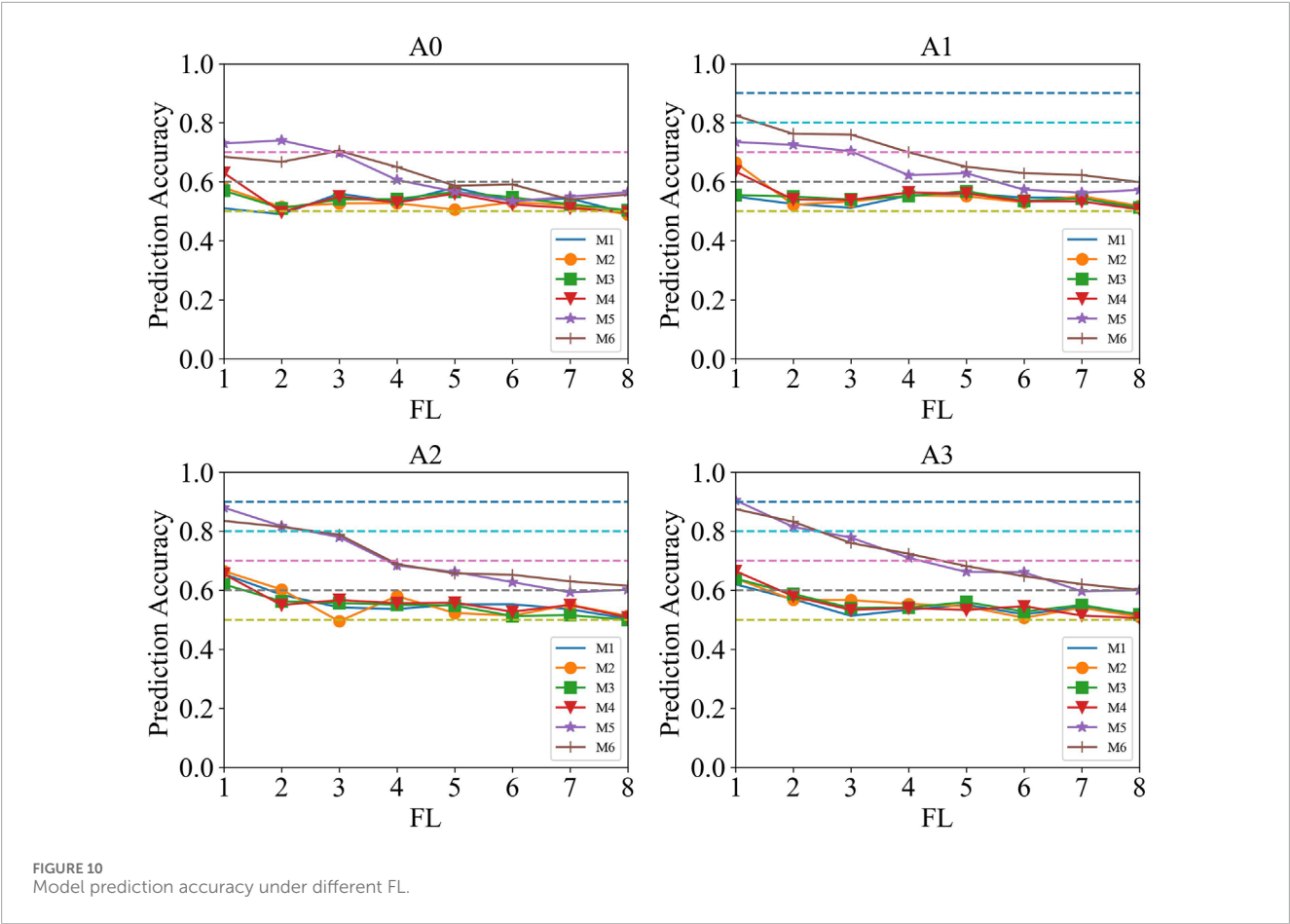


TABLE 4 Model parameter setting.

	Input layer dimension	Output layer dimension	Number of neurons in hidden layer	Batch size	Training rounds	Learning rate	Validate frequency
BP ₁	1	1	50	80	200	0.001	5
LSTM ₁							30
BP ₂	2						5
LSTM ₂							30

This paper provides a new perspective for the prediction of chaotic nonlinear systems and expands the application of entropy optimization within the field of e-commerce.

5.1 Result analysis

This study’s proposed approach for co-movement prediction in CS and SP yielded favorable results. Particularly the study innovatively puts forward entropy optimization guided by network features to enhance co-movement prediction. In our experiment, we construct CS-SP CN using time series data, and combine the designed forecasting rules with network features to form

bivariate co-movement forecasting based on rule combination for the first time. We call this novel approach RC-BCN. Comprehensive experiments show that the probability of establishing connections between highly similar modes is minimal in CS-SPCN. This may be attributed to the influence of nonlinear relationships, external variables, or temporal factors within CS-SPCN. The connection among co-movement modes is primarily influenced by node strength and edge weight in CS-SPCN. M-5 involves identifying the node with the strongest strength among the external nodes corresponding to the target node as the prediction outcome. In the case of M-6, the prediction outcome is determined by selecting the mode with the highest connection weight among the externally connected modes of the co-movement mode. These two

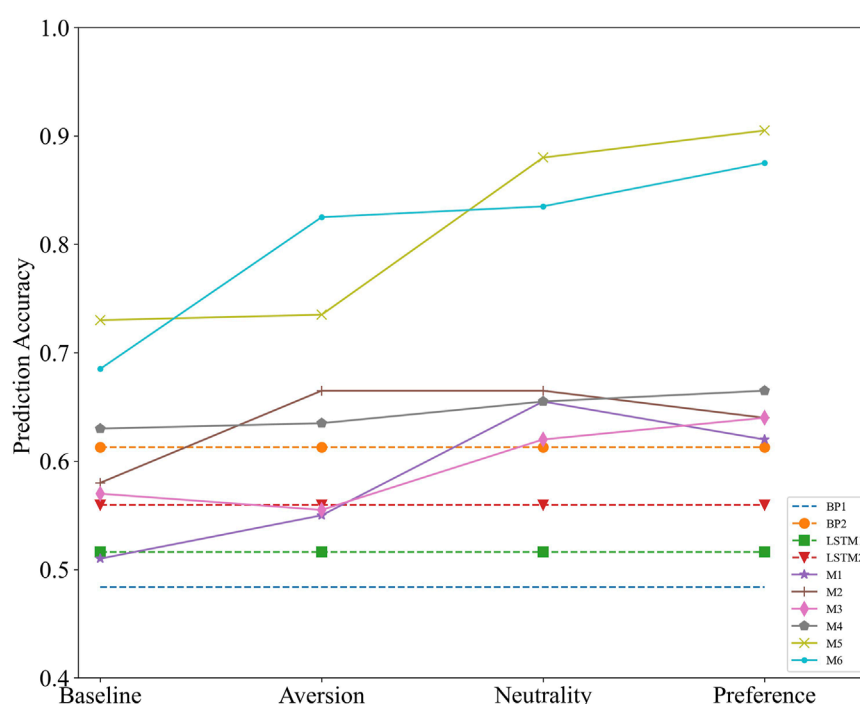


FIGURE 11
Prediction accuracy across different models when FL = 1.

models perform well. This demonstrates the effective integration of complex networks and entropy optimization into time series analysis, resulting in enhanced performance.

The sample size and data source may limit the generalizability of the results. Nevertheless, the JD platform and the electronic product categories selected in this study are representative, providing valuable insights into typical consumer behavior and financial market dynamics. Moreover, the robustness of the results has been verified using randomized experiments and sensitivity analysis (detailed in [Supplementary Appendix B](#)). To extend these findings, future research could explore enterprises across various industries, beyond just e-commerce, further validating and enriching the applicability of the proposed approach.

5.2 Theoretical and practical implications analysis

From a theoretical perspective, three outcomes are worth mentioning. Firstly, we delve into the co-movement between CS and SP on a finer time scale, providing valuable insights to support investor decision-making and corporate financing strategies. Secondly, we introduce a novel co-movement prediction model based on BCN and rule combination. Thirdly, we extend the application of entropy optimization in forecasting the co-movement between CS and SP, offers a new perspective on their relationship, and contributes to the development of entropy theory in economics.

Regarding practical contributions, the co-movement forecasting provides valuable insights for corporate financing and investor decision-making by revealing the intricate relationship between

CS and SP. For companies, leveraging this market feedback can help optimize financing strategies and assess potential risks. If negative sentiment is predicted to lead to a decline in stock prices, enterprises may opt to raise funds during periods of more favorable market sentiment, thereby reducing financing costs. For investors, understanding the predicted co-movement patterns, especially sustained opposite trends, can help them make more informed investment decisions and adopt appropriate risk mitigation strategies, ensuring cautious investment in volatile market conditions.

6 Conclusion and future work

In this study, we integrated complex network theory and entropy optimization into time series analysis, introducing a novel RC-BCN method to forecast the co-movement between CS and SP, which performs well. Additionally, the co-movement between CS and SP of JD is primarily driven by node strength and edge weight, suggesting that nodes and node pairs with higher frequencies of past appearances are more likely to reappear in the future. This indicates that the co-movement between CS and SP is influenced not only by the continuity of existing market behaviors and interaction structures, but also reflects the Matthew effect, that is, frequently occurring co-movement patterns are more likely to continue to dominate the co-movement in the future. Moreover, this study contributes a novel perspective and methodological framework for examining bivariate co-movement, offering significant implications for enterprises and investors in optimizing financing and investment strategies.

Similar to many studies, this research is not without its limitations. First, this study examines co-movement between variables in the same or opposite directions, but does not distinguish whether the co-movement in the same direction is positive or negative. Second, while many variables affect corporate financing and investment, this research focuses solely on two-variable co-movement prediction. Future studies will extend this method to forecast the co-movement among additional economic variables to enhance the generalizability of the findings. By incorporating the specific co-movement directions of each variable, both businesses and researchers can gain deeper insights into the interdependent relationships among complex economic systems in e-commerce.

Data availability statement

The original contributions presented in the study are included in the article/[Supplementary Material](#), further inquiries can be directed to the corresponding author.

Author contributions

MW: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Writing—original draft, Writing—review and editing. RK: Conceptualization, Supervision, Writing—review and editing. JL: Methodology, Writing—review and editing. WH: Writing—review and editing.

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Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fphy.2025.1557361/full#supplementary-material>

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