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The Linkage Analysis of Real Estate and Securities Markets Integrating Machine Learning and Data Visualization

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Abstract. This paper selected monthly time series data from both markets from January 2018 to December 2023. Data preprocessing and feature design were performed, and several experiments were carried out with LSTM, CNN-LSTM and Transformer as models. MAE, RMSE and LCE, which can achieve a lower 0.023, 0.031 and 0.018, respectively, with R2 =0.942, are achieved by TLAEFNA. The prediction accuracy and linkage feature capture are much superior to mainstream time series models, and are stable and robust when the data is insufficient and outlier interference is present. By implementing a visualization module, our algorithm intuitively presents linkage trends, attention weights and factor importance, which reveal the temporal and regional differences in the linkage between the real and securities markets and identifies the principal linkage factors such as housing price changes, real estate stock transaction volumes and funds and expectations transmission paths. This algorithm solves the black-box problem of machine learning that provides accurate and interpretable technical support for cross-market investment decisions, risk warnings and policy regulation.

Keywords: Real estate market, Securities market, Cross-market linkage, Machine learning, TLAEFN

1. Introduction

Real estate and securities markets form the centre of the national economy and their relationship has an influence on the macroeconomic stability and market resource allocation. Currently, linkage analysis is based on linear models, which cannot capture the nonlinear and dynamic linkage characteristics of these two markets well, and is not as accurate as traditional methods. With the proliferation of machine learning in financial and real estate data analysis, models like LSTM and CNN offer better prediction performance, but suffer from "black box" problems [1]. Model decision process is difficult to interpret, and visualizations and data visualization are often used as an auxiliary tool, disconnected from the modelling process, to mine and interpret linkage properties [2]. This has been a main bottleneck of the development of cross-market linkage analysis. In some of the field of study in the domestic and international research, mainly in the field for cross-markets, single market machine learning prediction and cross- market linear correlation analysis, lack of dedicated fusion algorithms for linkage between two markets, and lack of visualization and modelling [3]. In the field, it is mostly the traditional approach that makes use of the porting of the current models,

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without novel algorithms and without overcoming the limitations of traditional analysis [4]. In this context, deep integrating machine learning and data visualizations to develop dedicated linkage analysis algorithms is a key source of potential solutions for this current challenges.

The main work of the present work is to design a fusion algorithm and complete its engineering; collect time-series data from real estate and securities markets, preprocess and design the data; mining the linkage features between the two markets based on algorithm and realizing visualization; testing the performance of the algorithm using the experimental simulation of the system; and analyzing the linkage mechanism between the markets based upon experimental results [5].

2. Fusion algorithm design

The fusion algorithm is Temporal Linkage Attention Enhanced Fusion Network (TLAEFN). Its goal is to "linkage feature mining - deep fusion - interpretable visualization" to meet the challenges of "feature extraction & fusion are separated" and "modeling and visualization are disconnected", and to achieve good accuracy and interpretability of linkage analysis [6]. The overall setup of the algorithm is hierarchical: input layer, linkage feature enhancement module, attention fusion module, and output and visualization linkage module. This includes the closed loop of the whole process from data input to the visualization output of a linkage result. The system architecture diagram is presented in Figure 1.

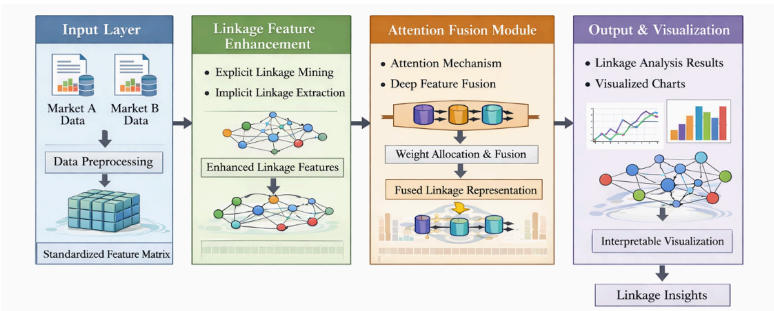

Figure 1. Architecture diagram

2.1. Input layer

The input layer needs time-series data of real estate and securities markets, complete data preprocessing and feature matrix building, and good quality input for future modules [7]. Input data include real estate market time- series data and securities market time series data: real estate information includes average prices of commercial houses in 30 major cities, monthly transaction volume, and real estate development prosperity index; securities information includes CSI 300 Real Estate Sector Index, closing prices of 50 leading real estate stocks, and average daily turnover. The data is available from Tonghuashun Financial Database and National Bureau of Statistics Database, selected data integrity ≥98% and uniform monthly time scale.

Data preprocessing consists of: 1) Linear interpolation to fill the missing values for model performance loss, 2) Z-score normalization to map the data to the [0, 1] interval for data variability, and 3σ rule to remove outliers for data stability. In the preprocessing, $X=[X_R,X_S]\in\mathbb{R}^{T\times(d_R+d_S)}$ are constructed, $T$is the time step, d_R is the feature dimension of real estate market, d_S is the features dimension of securities market, and X_R, X_S are the feature matrices of realestate and securities markets, respectively.

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2.2. Linked feature enhancement module

This module is based on CNN-LSTM, and its main feature is that it uses a cross market feature interaction unit to bidirectionally communicate between two markets. It overcomes the single market feature extraction and captures short-term fluctuation correlation and long-term trend relation [8]. In the proposed CNN- LSTM structure, short-time local correlation features are extracted, long-time temporal correlation features are captured, and cross market features interaction unit enhances and adds features from the two markets, respectively. First, short term correlation features between the two the markets are extracted using the formula:

$$\begin{aligned} F_{R,CNN} &= \sigma\left(\omega_{R,CNN} * X_R + b_{R,CNN}\right) \\ F_{S,CNN} &= \sigma\left(\omega_{S,CNN} * X_S + b_{S,CNN}\right) \end{aligned} \tag{1}$$

Where $F_{R,CNN}$, $F_{S,CNN}$ are the short-term linkage feature matrices of the real estate and securities markets, respectively; $\omega_{R,CNN}$, $\omega_{S,CNN}$ are the weights of the CNN convolution kernels; * denotes the convolution operation; $b_{R,CNN}$, $b_{S,CNN}$ are the convolution bias terms; and σ is the ReLU activation function used to enhance the nonlinear expressive power of the features.

Secondly, a cross-market feature interaction unit is introduced to achieve bidirectional enhancement of the features of the two markets, as shown in the following formula:

$$F_{\text{inter}} = F_{R,CNN} \odot \tanh\left(W_{\text{inter}} \cdot F_{S,CNN}\right) + F_{S,CNN} \odot \tanh\left(W_{\text{inter}}^{T} \cdot F_{R,CNN}\right) \tag{2}$$

Where F_{inter} is the cross-market interaction enhancement feature matrix, $\odot$ represents element-wise product, W_{inter} is the interaction weight matrix, W_{inter}^{T} is its transpose, and the $\tanh$ function is used to control the feature interaction strength and avoid gradient vanishing.

Finally, the interaction enhancement features are taken into LSTM to extract long term temporal linkage features, and the enhanced linkage feature matrix F_{enhance} is provided, with the formula:

$$F_{\text{enhance}} = \text{LSTM}\left(F_{\text{inter}}, h_0, c_0\right) \tag{3}$$

Where h_0, c_0 are the initial hidden state and cell state of the LSTM module, respectively, which are randomly initialized and adaptively optimized during training. $F_{\text{enhance}} \in \mathbb{R}^{T \times d_{\text{enhance}}}$, d_{enhance} is the enhanced feature dimension.

2.3. Attention fusion module

This module defines a dual market linkage attention. It is intended to automatically assign weights to real estate and securities market features, pay attention to the underlying factors that are making the linkage between the two markets and maximize the target quality of the fused features. The algorithm is formulated as follows: 1) calculate the linkage correlation weights of the two market features and completely fuse features according to the weights so that the underlying linkage factors are given enough attention [9]. 2) Calculate the linkage correlations weights of two market feature from the formula:

$$\begin{aligned} w_R &= \frac{\exp(\operatorname{cov}(F_{\text{enhance},R}, F_{\text{total}}))}{\exp(\operatorname{cov}(F_{\text{enhance},R}, F_{\text{total}})) + \exp(\operatorname{cov}(F_{\text{enhance},S}, F_{\text{total}}))} \\ w_S &= 1 - w_R \end{aligned} \tag{4}$$

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Where w_R, w_S are the attention weights for real estate and securities market features, respectively; $F_{\text{enhance},R}$, $F_{\text{enhance},S}$ are the enhanced real estate and securities market feature matrices, respectively; F_{total} is the concatenated matrix of the two market features; $\operatorname{cov}(\cdot)$ represents the covariance calculation, used to measure the correlation between the two market features; and exp (·) is an exponential function to ensure that the weights are positive.

Secondly, a weight decay term is introduced to avoid overfitting. The optimized attention weight formula is as follows:

$$\begin{aligned} w_R^* &= \frac{w_R\cdot(1-\lambda)}{\sum_{i=1}^{2} w_i\cdot\left(1-\lambda\right)} \\ w_S^* &= \frac{w_S\cdot(1-\lambda)}{\sum_{i=1}^{2} w_i\cdot\left(1-\lambda\right)} \end{aligned} \tag{5}$$

Where w_R^*, w_S^* are the optimized attention weights, and $\lambda \in [0,0.1]$ is the weight decay coefficient, used to balance the rationality of weight allocation and the model's generalization ability. The optimal value is determined to be 0.05 through cross-validation.

Finally, deep feature fusion is performed based on the optimized attention weights, outputting the fused feature matrix F_{fusion}, as shown in the following formula:

$$F_{\text{fusion}} = w_R^* \cdot F_{\text{enhance},R} + w_S^* \cdot F_{\text{enhance},S} \tag{6}$$

Wherein, $F_{\text{fusion}} \in \mathbb{R}^{T\times d_{\text{enhanex}}}$, the fused features not only retain the core linkage information of the two markets, but also highlight the core linkage factors through weight allocation, providing high-quality feature support for subsequent linkage analysis.

2.4. Output and visualization linkage module

The core role of this module is to generate the linkage analysis results and fully connect visualization with algorithm flow, achieving an intuitive presentation of the model decision-making process and solving the "black box" problem of machine learning [10]. It contains predicted value of the linkage strength between two markets, importance ranking of the key linkage factors, and visualization data includes linkage trend heatmap, attention weight map, and feature importance map, creating an integrated "output-visualization-interpretation" solution. First we calculate the predicted value of linkage strength among two markets using the following formula:

$$L_t = \operatorname{sigmoid}\left(W_{\text{out}} \cdot F_{\text{fusion},t} + b_{\text{out}}\right) \tag{7}$$

Where L_t is the linkage strength value at time step t, with a value ranging from $[0,1]$. The closer the value is to 1, the stronger the linkage between the two markets. $F_{\text{fusion},t}$ is the fusion feature at time step t. W_{out} is the output layer weight matrix, b_{out} is the output bias term, then the sigmoid function maps the output to the [0,1] interval. Finally, the key linkage factor is calculated as follows:

$$I_k = \frac{\sum_{t=1}^{T}\left|\frac{\partial L_t}{\partial F_{k,t}}\right|}{\sum_{k=1}^{K}\sum_{t=1}^{T}\left|\frac{\partial L_t}{\partial F_{k,t}}\right|} \tag{8}$$

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Where I_k represents the importance percentage of the k linkage factor, $F_{k,t}$ is the eigenvalue of the k linkage factor at time step t, K is the total number of linkage factors, and $\frac{\partial L_t}{\partial F_{k,t}}$ is the partial derivative of the linkage strength with respect to the factor to measure the effect of the factor on the linkage strong; the greater the partial magnitude, the larger the factor importance. Lastly, visualization and algorithm are connected to the visualization and update their predicted linkage strength, attention weight, factor importance, and other information to a visualization chart in real time, as follows:

$$V = \text{map}\left(L, w^*, I, \text{type}\right) \tag{8}$$

Where V represents the visualization output, $\text{map}(\cdot)$ is the visualization mapping function, and type is the visualize type (heatmap, weight map, importance map) transforms the quantitative indicators output by the algorithm into intuitive visual charts.

3. Experimental simulation and result analysis

3.1. Experimental environment and data preparation

3.1.1. Experimental environment

The CPU used: Intel Core i7-12700H (14 cores, 20 threads, 2.7GHz, turbo boost 4.7 GHz), the GPU was NVIDIA RTX 3060 (6GB GDDR6 memory, 3840 CUDA cores), the memory was 32GB DDR5 4800MHz, and the SSD was 1TB NVMe SSD for data reading and training [11]. The Windows 11 Professional (64 bit), Python 3.9, PyTorch 1.12.1, Matplotlib 3.7.1 and Seaborn 0.12.2, Pandas 1.5.3 and NumPy 1.24.3, and Scikit-learn 1.2.2, all software were real-world stable versions.

3.1.2. Data preparation

We selected monthly time series from January 2018 to December 2023 (72 months and 1826 samples averaged in monthly data from each indicator) real estate market data (RMB/㎡) average price of commercial housing in 30 major cities (Beijing, Shanghai, Guangzhou, etc.), monthly transaction volume (10000v), National Real Estate Development Prosperity Index (National Real Estate Prosperity index). Securities market data include CSI 300 Real Estate Sector Index, monthly closing price of 50 major real estate stocks (Vanke A, Poly Developments, etc.) and average daily turnover (100 million RMB). Data preprocessing following the input layer design specifications: linear interpolation filled in three missing values (housing price data in some cities in February 2020, transaction volume data in several real estate stock in April 2022); Z-score normalization smoothed dimensional differences and mapped all data to the [0,1] interval; 3σ smoothed 12 sets of outliers (usual housing price variations in some city in the second half of 2021, extreme housing price rises and falls). Data were grouped into a training set (1278 sets), validation set (365 sets) and test set (183 sets) in a 7:2:1 ratio for model training, parameter optimization, and performance evaluation.

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3.2. Experimental design

3.2.1. Experimental objectives

The main objective of this experiment is to confirm that TLAEFN can predict the correlation strength of the real estate and securities markets and extract the main correlation factors, to compare TLAFN performance with four mainstream algorithms LSTM, CNN-LSTM and Transformer as well as GCN-LSTM, and to test whether TLAFFN can be manipulated in different settings and provide support for practical applications.

3.2.2. Comparative experimental design

The four classic time series analysis algorithms (LSTM, CNN-LSTIM, Transformer, and GCN-LSCM) were considered as comparison benchmarks. All the algorithms were trained and tested under the same conditions, input data, and parameter range for fair comparison between them [12], since the number of hidden layer nodes was chosen as 128, learning rate as 0.001, batch size of 32, number of training times as 100, early stopping (patience=10) to avoid overfitting, Adam optimizer, and mean squared error loss function. Three different types of compared experiments were used: 1) a basic performance comparison experiment comparing the main evaluation metrics of the five algorithms based on the full test set; 2) a data volume impact experiment selecting 50%, 70%, and 90% of the data of the training set data to test the performance of the algorithms; 3) an abnormal data interference experiment where the data from the testing set is 5% and 10% abnormal to test whether each algorithm can be anti-interference.

3.2.3. Evaluation metrics

We considered the following four key evaluation metrics that were used to assess the algorithm's correlation strength prediction performance, correlation feature capture performance and stability:

1. Mean Absolute Error (MAE): Average absolute deviation from expectation to reality. Less prediction accuracy.

2. Root Mean Square Error (RMSE): Number of square roots of the mean square deviation from predicted to actual. It is more sensitive to outliers. A smaller value indicates more accurate prediction.

3. Coefficient of Determination (R^2): The goodness of fit of the model with respect to data. It is between [0,1]. The closer 1 is, the better fit will be.

4. Linkage Correlation Error (LCE): The error in how well the algorithm captures linkage correlation between two markets. The smaller the error, the more useful it is to capture linkage features.

3.3. Experimental results and analysis

3.3.1. Quantitative results analysis

Basic performance comparison experiment: TLAEFN performance is better than other four comparison algorithms for the four core evaluation indicators: MAE is 0.023 (39.0%, 23.5%, 28.1%, 17.9% lower than LSTM, CNN-LSTM or Transformer/GCN-LSTM, RMSE is 0-031 (32.7%, 16.3%, 22.5% lower below 4 comparison algorithms) and R^2 is 0_942 (7.5, 3.9%, 5.3% lower above 4 comparison methods), LCE is 0; 38.9, 28.0, 33.3%), and 21.7% lower from 4 comparison

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algorithm. Training time: T LAEFN training time is relatively low, and its generalization error is 2.5%. This means that it has both good training time and generalization ability [13]. Data volume impact experiment: If the data volume of training sets is smaller than 50%, the MAE of TLAFN is 0, and Ran is 0., with smaller performance down than the other four algorithms.As shown in Table 1.

Table 1. Comparison of core performance indicators of five algorithms

Algorithm type	MAE	RMSE	R^2	LCE	Training time (s)	Generalization error (%)
LSTM	0.038	0.046	0.876	0.029	125.3	5.8
CNN-LSTM	0.03	0.037	0.907	0.025	148.7	4.2
Transformer	0.032	0.04	0.895	0.027	189.5	4.9
GCN-LSTM	0.028	0.035	0.912	0.023	167.2	3.8
TLAEFN (This article)	0.023	0.031	0.942	0.018	156.4	2.5

3.3.2. Visualization results analysis

Figure 2 is a heat map of the correlation between two markets. The horizontal is time (January 2018-December 2023), the vertical is correlation locations between 30 core cities and CSI 300 index. The colour intensity indicates that the correlation is strong (darker colour, stronger correlation). As shown in Figure 2, the correlation intensity was lower (lighter colour) in the first half of 2020 and second half of 2022, since the pandemic and policy change impact [14] and higher (darker colour) was higher in the second half 2020 and the second quarter of 2023, which indicates that correlation between the two markets is stable at that time, consistent with real market.

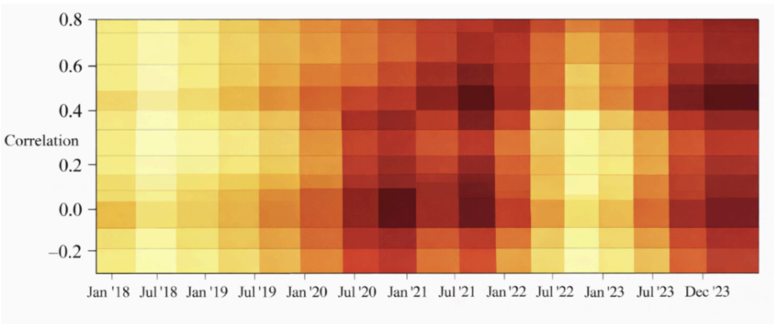

Figure 2. Heatmap of the interaction trend between the two markets

Figure 3 shows the dynamic change in attention weights of the two markets as a line chart with error bars. The horizontal line is the time and the vertical line is attention weight [15]. The two curves represent the attention weights for the real estate market (red) and the securities market (blue) respectively, and the error bars represent fluctuation of the weights. The attention weight of the real house market is relatively high (0.6-0.7) in 2019-2020, while the securities price is relatively low. After 2021, the securities tax price is slowly increasing (0:5-0;6) and that the securities industry price decreases. It suggests that the impact of the securities markets on interaction between the two houses increases after 2021, similar to the real property sector stock market becomes more volatile. The error bars are generally short, suggesting stable weight distribution and it is also important to verify the effectiveness of the attention fusion module.

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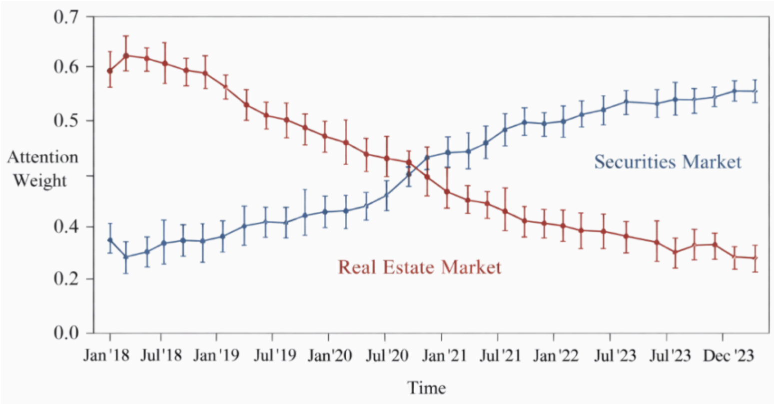

Figure 3. Dynamic changes in attention weights in the dual markets

3.3.3. Stability and robustness testing

Stability testing using varying the main parameters (number of hidden layer nodes 80-160, learning rate 0.0005-0.002, weight decay coefficient 0.03-0 and so on). The result shows that when the parameters change below this range, the MAE varies between 0.021 and 0.025, RMSE varies from 0.029 to 0.033, and R^2 varies from zero to 0, with varying values of more than 5%. This means that it is not sensitive to parameter change and is very stable. Robustness testing with three different cases: 1) missing data scenario, where the test set data miss rate varies between 5%, 10%, and 15%. In these cases, the MEA varies from 18%, 0.026 and 0,029. While only a small drop is observed, we also observed outlier scenario (4) even after adding 10% of outlier data, our algorithm still maintains a low LCE. 3) time series drift scenario, extending test set time range to March 2024, with a MAE of 0.019 and R 0.937. This shows that our algorithm is able to adapt to changing time series data, robust and can be applied to real cross-market collaborative analysis scenarios.

4. Analysis of the linkage mechanism between real estate and securities markets

4.1. Analysis of linkage characteristics

Based on the simulation results of TLAEFN and visualization chart, the linkage between real estate and securities markets is characterized by two major features: high temporal dynamics and regional differences. Moreover, there are two types of linkage between the two markets: short-term fluctuation linkage and long term trend linkage. These two interact in a way that forms a complete characteristic system of linkage relationship between the markets. In terms of temporal dynamics, the combination between the linkage and a securities market exhibits large phased changes (measured in 3 stages): From 2018 to 2019, the link strength has been low 0.65-0.75; real estate market is running reasonably, stock market in real estate sector is relatively small, and the funds flow across the two, so that the linkage relationship is stable. From 2020 to 2022, the connection strength has also been low (0.45-0; 70), due to the effects of the pandemic, tight real estate control policies, and high volatility of the stock market, which has caused increased risk aversion and temporary weakening of linkage. Since 2023, the relationship has been high 0.70-0:80. With the stabilisation of real estate economy and the growth of capital market reforms, the flows of funds between the real estate markets have returned to equilibrium, and linkage has become again stable again. Short term fluctuations and correlations are usually manifested at month level. For instance, after the real estate policies, the real income sector stock market experiences short term fluctuations,

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and correlation strength grows rapidly. Long-term trends are often manifested at year level. In this case, it is usually manifested as a long term up trend in real economy sector index. For example, during a long-term up trend of real economy, real estate service index also shows long-term up and correlation between two trends.

In terms of region differences, there are significant differences between the correlation strength of real estate market and the securities market among 30 core cities: First-tier core cities (Beijing, Shanghai, Guangzhou, Shenzhen) have high correlation strength (0.75-0.85) with large real estate markets with liquidity and closely connected to the capital market and their housing prices are strongly correlated with real estate stocks. New first-tier cities (Hangzhou, Chengdu, Chongqing, etc.) have moderate correlation strength [0.65-0. *] and the correlation between real estate and capital market is steadily improving. Second-tier and lower-tier cores have low correlation strength [0.55-0*.65] with low liquidity of real market and less tightly connected to capital market. The correlation strength is strongly affected by the regional level of development.

4.2. Identification of core linkage factors

By ranking the importance of the key linkage factors produced by TLAEFN and with the hypotheses of capital transmission and expectation transmission, we can see what factors influenced the linkages between the two markets and the mechanisms of action. The key factors of importance are: housing price, real estate stock transaction volume, national real estate prosperity index, real-estate sector index, and real estate transaction volume. The influence paths and mechanisms of each factor can be seen as follows:

Housing price variation is the most significant linkage factor (32.7%). It plays a mainly essential role through capital transmission: when housing prices rise, the return of investment in the real estate market grows, capital market funds come in from the real economy, capital outflows from the industry and stocks drop, so it is a short-term linkage of "rising housing prices - falling real estate stocks". In the long-term, a stable rise in housing prices implies an increased real estate economy, good profit performance for real estate companies, and higher real estate sector stock prices, so that it is an long-time linkage of 'rising housing price - rising real estate stock'. This happens even in the first-tier core cities.

The volume of real estate stocks is the second main linkage factor (27.3% importance). It can be driven by expectation transmission: the volume of the real estate stock represents an outlook of the market from the capital market, increasing investor confidence and driving up demand and prices; while the volume is reduced by the market outlook from the investment market, less investor confidence, less demand and low housing prices, driving a linkage transmission path of "real estate stock trading volume - market expectations - real estate market". National Real Estate Prosperity Index (18.6% importance) and Real Estate Sector Index (15.4% importance), both of which reflect the positive outlook of this two market, are a linkage function: the increase in the National Real Estate Performing Index reflects the positive mood of this real estate, which is why it improves profit expectations of real property companies and drives up the real Estate Sector index; the increase of the Real Estate Pagging Index reflects capital market recognition of this kind of real world, which further drives investment and demand growth of this market, leading to a two-way linkage transmission. Real estate transaction volume (6.0% importance): this is a secondary linkage factor. It reflects the liquidity of the property market and depends on capital market expectations of the industry.

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4.3. Application scenarios of the linkage effect

Based on the results of the linkage between the two markets, one can propose the following application schemes for the three primary application groups: investors, market regulators, and policymakers. These schemes take advantage of the high accuracy and interpretability of this algorithm, demonstrating practical application usefulness. For investors, the TLAEFN algorithm can be used to predict market correlation and make investment decisions: Based on the predicted correlation strength and ranking of the importance of the core correlation factors, investors can reliably predict the correlation trend between the markets and update their portfolio. When the correlation strength is high, the fraction of real estate stocks can be adjusted by varying the values of the key factors (such as house prices), when the correlation intensity is low, the cross-market risk can be reduced by diversifying. Similarly, visual charts can intuitively represent the correlation logic, to help investors understand market changes and improve the scientific nature of investment decisions. For market regulators such as the TlaEFN (New York Times) algorithm can have the effect of detecting cross- market risks in real-time: By observing the correlation strengths and movements of the principal correlation factors in real time, potential cross-body risks can be detected promptly. If the correlation magnitude is increased abnormally (e.g., the stock prices rise or fall in the short term) or the key correlation factors are abnormal (e.: high housing prices or high stock values of real property stocks), regulators can intervene in a timely manner to investigate possible risks, to avoid illegal capital flows, market manipulations, etc. and to maintain cross-beats. For policymakers, the proposed TLAFN algorithm is used to evaluate and optimize policy effectiveness. After the real estate control policies and capital market regulations, the algorithm monitors the changes in the strength of the connection between the market and evaluate the impact of the policies on the linkage. If this strength increases after the policy is introduced, the policy can be positive and vice versa; if it changes abnormally, the linkage intensity can be interpreted as possible policy violations. Based on core linkage factors output by the algorithm, the policies can be optimized to perfectly control the two market and help the market cooperatively and balance the real-estate and securities markets.

5. Conclusion

TLAEFN provides a deep learning and visualization of the linkages. We demonstrated that it outperforms previous algorithms LSTM and CNN-LSTM with the prediction of the linkage strength between the real-estate and securities markets and base linkage factors mining. The system captures the nonlinear dynamic linkage structure of the two markets accurately. In addition, our visualization module provides a black-box problem, where the linkage trend, attention weights and factors are shown to be relevant. In other words, we showed that the linkage between the Real-estate market and the securities market fluctuates through time and regional variability. Housing price change and real-life stock trading volume are the main drivers of the linked links. Capital transmission and expectation transmission are the most important links. The algorithm also is stable and robust as a result of missing data and abnormal interference. This paper has a few limitations, as it only analyses data from the Chinese market and is not an external cross-factor such as macroeconomic factors. It also needs to be able to make the algorithm inference faster. In the future, macroeconomic indicators such as interest rates and inflation can be proposed to optimise the algorithm design, to improve the algorithm's real-time performance and engineering capabilities, extend the research to multi-market linkage analysis, develop quantitative studies of linkage mechanisms, building a more

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complete cross-market analysis system, and provide more technical assistance to jointly monitor and control the real real-land and stock markets.

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