The Dynamic Correlation Between News Sentiment And Housing Price Volatility: A Heterogeneity Perspective

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Based on the differences between traditional news and digital news, this paper takes a heterogeneous perspective to systematically analyze the dynamic correlation degree, time-varying impulse response, and spillover effects between traditional news sentiment, digital news sentiment, and housing price volatility using DCC-GARCH model, TVP-SV-VAR model, and Spillover Index model. Through the application of machine learning techniques, the research results are obtained: (a) The correlation between the three variables exhibits significant temporal variability, especially in the later stage of the sample period. (b) There is a positive dynamic correlation between news sentiment from two different sources, and housing price volatility is significantly affected by spillover effects from both types of news sentiment. (c) Traditional news sentiment dominates in the early stage of the sample period, but its influence gradually fades in the later stage. In contrast, the positive impact of digital news sentiment on housing price volatility is more sustained. We believe that in the current context of diversified development in the media industry, policy makers should pay attention to the complex dynamic correlation between different news sentiment and housing price volatility. While focusing on regulating digital media, the influence of traditional media cannot be ignored.

Keywords: News sentiment; housing price volatility; heterogeneity analysis; TVP-SV-VAR model; DCC-GARCH model; Spillover Index model

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1. Introduction

The efficient markets hypothesis holds that in an ideal market, asset prices are the sufficient reflections of all available information. However, the actual market is often affected by information asymmetry and participant behavior, resulting in prices not fully reflecting all available information. Black [1] found that market investors could profit from noise deal. De Long et al. [2] found that irrational trading by noise traders could easily lead to asset price deviations. Shiller [3] found that stock prices generally exhibited significant volatility, and the efficient markets hypothesis was difficult to fully explain this phenomenon, indicating that asset prices were influenced by other factors. Obviously, prices cannot reflect all useful information in the market. The media is the most convenient way for investors to obtain information due to its advantages of fast dissemination speed, wide coverage, and low cost. In addition to prices, the media also reflects key information in the capital market.

With the rapid development of information technology, the role of news media in influencing the financial and real estate markets is becoming increasingly important. Especially the sentiment contained in the information it conveys may directly affect investors' expectations and decision-making behavior, thereby having a significant impact on asset prices.

In recent years, the academic community has conducted extensive research on the correlations between news sentiment and financial market volatility. Tetlock [4] believed that news content had a significant impact on investor sentiment, and this impact could significantly change stock prices in the short term. Tetlock et al. [5] found that financial media content captured the difficult to quantify aspects of a company's fundamentals, which could be quickly reflected in stock prices by investors. Schumaker et al. [6] evaluated financial news sentiment using the AZFinText system and examined the impact of author sentiment on predicting future stock price trends. They found that articles with negative sentiment were the easiest to predict price trends, and there was an inverse relationship between sentiment polarity and stock price trends. Li et al. [7] argued that financial news had an impact on stock price returns, and experiments had shown that sentiment analysis could improve the accuracy of stock price predictions. Li et al. [8] used a media aware trading strategy to quantify the information dissemination mechanism and examined the impact of digital media on the stock market. They found that basic information and sentiment in digital news could affect investors' trading activities and decisions. Li et al. [9] proposed a new model that combined machine learning and sentiment analysis, which improved the accuracy of stock market predictions by comprehensively processing sentiment analysis of news articles and historical data of stock prices. Seong and Nam [10] improved the accuracy of sentiment analysis by segmenting financial news, thereby enhancing the accuracy of stock trend prediction models. Fazlija and Harder [11] believed that models combining financial news sentiment with historical price data performed more accurately in predicting stock price trends. Khan et al. [12] found that a model that combined social media and news data significantly outperformed models that only used traditional market data in predicting stock market trends.

Research on financial markets has shown that media coverage can trigger market volatility or trend changes. The real estate market, which is similar to it, also relies on the dissemination of information and is sentiment-based with high potential. Therefore, the correlation between news sentiment and the real estate market has gradually attracted the attention of some scholars. Lambertini et al. [13] found that news shocks could trigger an inverted Ushaped response in housing prices, and both news and expected shocks together explained the majority of the variance in housing price prediction errors. Walker [14] found no significant correlation between the number of media reports and UK housing price volatility, but there was a significant Granger causality relationship between media sentiment and housing prices. Yang and Seng [15] constructed a news sentiment rating model to verify the correlation between news sentiment and housing prices, and found that news sentiment could serve as a reference indicator for evaluating housing price trends. Soo [16] also found that news media sentiment had a significant leading role before changes in housing prices, and he analyzed the role of sentiment index in different characteristic markets. Beracha et al. [17] obtained evidence that news sentiment could serve as an early market indicator in the US commercial real estate market, and Ploessl and Just [18] reached a similar conclusion in the German residential real estate market. Overall, the impact of news sentiment on the market has received widespread attention from scholars. However, the existing research on the real estate market is not nearly as mature and deep as that on the financial market. Especially in terms of comparing and analyzing the correlation between news sentiment from different sources and the real estate market from a heterogeneous perspective, the related research is still relatively scarce and urgently need to be filled.

Traditional news sentiment is mainly transmitted through newspapers, radio and other traditional media channels, while digital news sentiment relies on the rapid dissemination and real-time interaction of Internet platforms. These two types of news sentiment not only differ in terms of information dissemination speed, breadth, quality, and emotional expression, but also probably exhibit heterogeneity on their impact path and intensity on the market.

In recent years, the network media relying on mobile communication technology and Internet technology has developed rapidly, and quickly seized the market with its advantages of low cost, high efficiency and convenience, becoming an important force that cannot be ignored in the media industry, and constantly impacting the traditional media industry. Like other more developed economies, traditional media in China is generally declining. On the one hand, the number of newspaper publications is decreasing, and the overall scale is shrinking. Since 2017, much print media has suspended publication. Taking 2020 and 2021 as examples, more than 30 and 20 well-known newspapers and magazines announced their suspension of publication. On the other hand, the printing quantity and sales volume are also continuously declining, with the total printed pages of newspapers in 2021 decreasing by 4% compared to 2020 . The emergence of digital media has begun to change people's reading means and habits. People are more willing to browse information directly online, which is not only convenient and fast, but also reduces reading costs, and is highly welcomed by readers. However, traditional media remains the mainstream in the media industry because it still has many irreplaceable advantages. Firstly, the specialized news team of traditional media is beyond the reach of much digital media, making it superior in terms of depth, breadth, and height of news reporting. Secondly, the credibility and authority of traditional media are established in the minds of users over the long term. According to a survey report on the credibility of digital media released by the Chinese Ministry of Industry and Information Technology, users' satisfaction with the seriousness and authority of digital media is not optimistic.

The housing price volatility is an important variable in the macroeconomic field, which is not only related to the stability of financial markets, but also closely related to residents' wealth, consumption, and investment. The housing price volatility, in addition to traditional supply and demand factors Fan [19], may also be influenced by market participants' psychological expectations [20–22], policy orientation [23, 24], and information shocks [25]. Understanding the dynamic correlation between news sentiment and housing price volatility, especially the heterogeneity impact between different sentiment sources, can provide decisionmakers with more comprehensive policy basis and help investors and market analysts better grasp the risks of market fluctuations.

The diversified development of news media has made the impact of news sentiment on housing price volatility increasingly complex. Thus, we wonder: Is there a spillover effect between news sentiment from different sources? Are the degrees of correlations between them and housing price volatility different? Are the correlations between them dynamic? In the previous discussion, these issues above are not focused. The reasons of the overlook may be complex, and one of the reasons is the difficulty of mining and understanding semantics in news. After all, it is inefficient and unrealistic to manually read numerous news. Fortunately, with the development of machine learning [26], news semantic mining is now an easier work than before [27]. In fact, the machine learning technique can promote almost all research fields, such as object detection [28] and enterprise management [29]. In these conditions, to address these issues above, we take Beijing, the capital of China, as an example to conduct the research in the paper. Firstly, we developed a Python program to collect traditional and digital news reports related to housing prices from January 2011 to December 2022; Then, with the help of increasing machine learning technique in mining and understanding semantics in news [30, 31], we used natural language processing technology to quantify news sentiment; Finally, we utilized Dynamic Conditional Correlation - Generalized AutoRegressive Conditional Heteroskedasticity (DCC-GARCH) model, Time Varying Parameter - Stochastic Volatility - Vector Auto Regression (TVP-SV-VAR) model, and Spillover Index model to analyze the dynamic correlations, impulse response, and spillover effects between traditional news sentiment, digital news sentiment, and housing price volatility. The results of the three models were progressively validated by each other.

The possible contributions of this paper are as follows. Firstly, this paper examines the dynamic correlations and spillover effects between news sentiment from different sources and housing price volatility from a heterogeneity perspective, which fills the gap in existing research. Secondly, the empirical analysis method adopts a strategy of combining three methods, gradually deepening and progressing layer by layer, to systematically analyze the correlations between news sentiment and housing price volatility, which enriches the empirical research on housing price volatility. Finally, the research findings of this paper are not only crucial for revealing the mechanism of housing price volatility, but also provide forward-looking risk prevention reference for policy makers and market participants. The rest of this paper is organized as follows. Section 2 provides a detailed introduction to research methods and materials in this paper. Section 3 reports the empirical analysis results, conducts further analysis, and provides appropriate suggestions. Section 4 summarizes the entire paper.

2. Methods

2.1. Model

The empirical analysis methods used in this paper are DCC-GARCH model, TVP-SV-VAR model, and Spillover Index model. Firstly, in order to examine the interdependence between variables, we used the DCC-GARCH model [32] to measure the dynamic correlation between variables. Then, in order to further reveal the dynamic transmission relationship between variables, we used the TVP-SV-VAR model to analyze two types of impulse responses between variables, namely impulse response analysis in different lag periods and impulse response analysis at different time points. The TVP-SV-VAR model, by allowing model parameters to vary over time and combining them with random volatility, can flexibly capture the time-varying dynamic relationships between variables, making it particularly suitable for processing time series data that exhibit different dynamic characteristics at different time periods [33, 34]. Finally, we used the Spillover Index model [35] to decompose the variance contributions of each variable, measure the degree of information transmission between different variables, and provide intuitive quantitative results about spillover effects. By combining the application of these three methods, this paper can comprehensively reveal the interaction and dynamic evolution characteristics between traditional news sentiment, digital news sentiment, and housing price volatility.

2.2. Data

The sample data for this paper comes from Beijing, which is the capital city of China and the core city for policy formulation and implementation. The real estate market is deeply influenced by the country's macroeconomic regulation policies and has strong policy sensitivity. Taking Beijing as the research object not only achieves the research purpose of this paper, but also reveals the impact of regulatory policies. In addition, the data of Beijing's real estate market and news reports are relatively complete and of high quality, which facilitates accurate empirical analysis. Therefore, focusing on Beijing can better capture the relationships between variables and provide valuable references for real estate research in other cities. The traditional news text data comes from the DuXiu database, a super large academic search engine, which includes and continuously updates more than 1000 important party newspapers, industry newspapers, and comprehensive newspapers at all levels in China. However, this database does not include online news data. Correspondingly, the online news text data is from WiseSearch database, which includes news information from over 8000 websites in China. Additionally, the monthly housing price index in Beijing is taken from the Housing Price Index released by the National Bureau of Statistics of China. This paper contains three variables, namely traditional news sentiment (TNS), digital news sentiment (DNS), and housing price volatility (HPV). The HPV in this paper is the volatility rate of housing prices calculated by seasonally adjusting the monthly housing price index in Beijing using the Census X-12 multiplication model and then using HP filtering. The research period of this paper is from January 2011 to December 2022, a total of 144 months. We collected a total of 7903 traditional news and 84837 digital news using "Beijing housing prices" and "first tier city housing prices" as keywords. After data preprocessing, we retained 6476 traditional news and 75462 digital news, totaling 81938 news. The news sentiment analysis adopts a machine learning based sentiment analysis model that has undergone sufficient training. The detail analysis process is shown in Fig. 1. First, the retained news text data is segmented as words according to dictionaries. Then, the words are converted into word embedding vectors. Finally, a full connected network is trained via stochastic gradient descent on the basis of a small proportion labeled words to be used in the prediction of the sentiment scores of those word embedding vectors. The score range for news sentiment is 0 to 1 , with 0-0.4 indicating negative sentiment, 0.4-0.6 indicating neutral sentiment, and 0.6-1 indicating positive sentiment. The calculations of TNS or DNS are shown in Eq. 1.

$$S_t = \frac{N_t^{\text{pos}} - N_t^{\text{neg}}}{N_t^{\text{pos}} + N_t^{\text{neg}} + 1} \tag{1}$$

where S_t represents the TNS or DNS during period (month) t; N_t^{pos} stands for the count of traditional or digital positive sentiment news reports in period (month) t; and N_t^{neg} stands for the count of traditional or digital negative sentiment news reports in period (month) t.

2.3. Data Statistics

The descriptive statistics of the three variables are shown in Table 1. In addition, before conducting empirical analysis, we used the Augmented Dickey Fuller (ADF) and Phillips Perron (PP) test to test the stationarity of the variables. The ADF and PP test results are also shown in Table 1, where *** indicates statistical significance at the 1% level.

From the means of the two types of news sentiment, it can be seen that news about housing prices generally reports more negative sentiment than positive sentiment, especially in traditional news media. The reason is that the irrational growth of housing prices in Beijing has caused concerns from the government and media for a long time. From the standard deviation (SD) values, the fluctuation range of housing price volatility is the largest, followed by digital news sentiment, while traditional news sentiment has relatively small fluctuations. The ADF and PP test results show that all three variables are stationary time series.

3. Results and discussion

3.1. Dynamic Correlation Coefficient Analysis Based on DCC-GARCH Model

Engle's DCC-GARCH model can be effectively used to describe the dynamic correlations between multiple time series. The calculation of DCC-GARCH model is divided into two steps: (1) Establish a univariate GARCH model for each variable and divide the residuals by the conditional

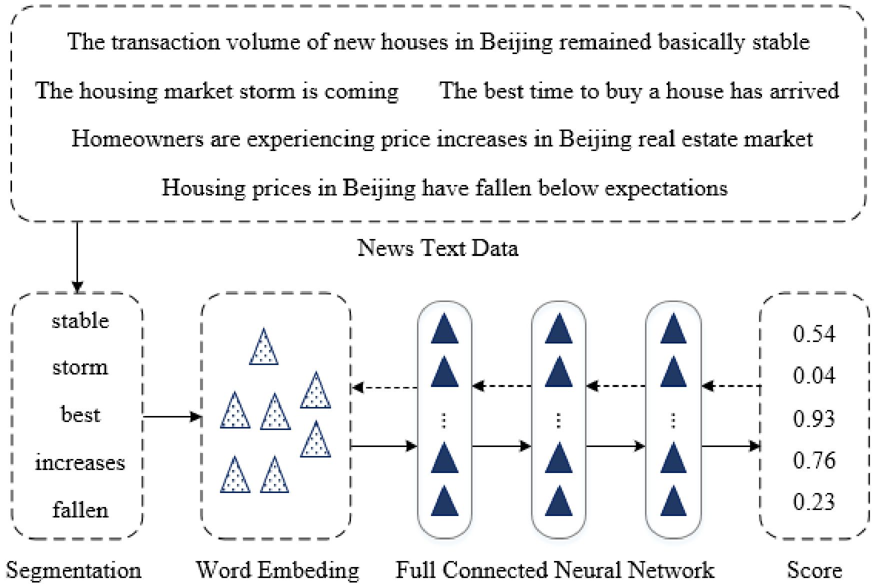

Fig. 1. Machine learning based news sentiment analysis model.

Table 1. Summary statistics for all variables

Variable	Mean	Median	Maximum	Minimum	SD	ADF test	PP test
TNS	-0.316	-0.400	0.853	-0.938	0.452	-4.086***	-8.387***
DNS	-0.071	-0.114	0.964	-0.979	0.622	-5.532^{***}	-5.600^{***}
HPV	4.38×10^{-12}	-0.078	4.095	-1.980	0.784	-4.646^{***}	-4.582^{***}

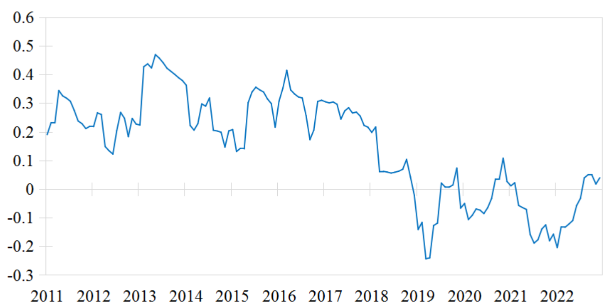

Fig. 2. Dynamic correlations between TNS and HPV

variance to obtain a standardized residual sequence. (2) Calculate the dynamic conditional correlation coefficient using the standardized residual sequence obtained in the first step.

The dynamic correlation coefficients between HPV, TNS, and DNS variables are shown Fig. 2, Fig. 3 and Fig. 4, indicating a significant temporal variability in the correlation coefficients between the variables. Fig. 2 shows the dynamic correlation coefficients between traditional news sentiment and housing price volatility. Numerically, their correlation coefficients are distributed between -0.244 and 0.469. In terms of directions, they were positive before 2019 and basically negative after 2019, except for a few time points. The two obvious peaks in the positive direction occurred in May 2013 and March 2016, which corresponded to the period before and after the relaxation of China's real estate regulation policies (2014-2016). The positive correlation between traditional news sentiment and housing price volatility has weakened since 2017, and has even turned negative since 2019. The reason may be that China's real estate policy has shifted again since 2017, entering a new round of regulation. During this period, traditional media may focus more on the social pressure or negative impact of rising housing prices, rather than short-term market volatility. In addition, this phenomenon is also related to the impact of digital media on traditional media. Fig. 3 shows the dynamic correlation coefficients between digital news sentiment and housing price volatility. It is evident that there is a positive correlation between the two throughout the entire sample period.

Numerically, the range of correlation coefficients is between 0.178 and 0.238. In terms of trends, the positive

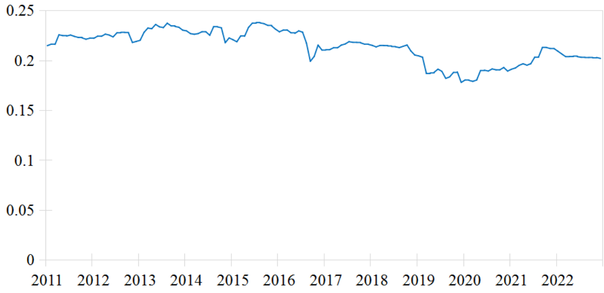

Fig. 3. Dynamic correlations between DNS and HPV.

Fig. 4. Dynamic correlations between TNS and DNS.

correlation coefficients between digital news sentiment and housing price volatility during the relaxation period of China's real estate market regulation (2014-2016) are greater than those during the real estate market regulation period (2017-2021). This indicates that when policies are relaxed and the market is active, digital news more actively reflects the housing price volatility. While during the regulation period, this positive correlation weakens, reflecting the constraining effect of policies on the market. Furthermore, from the peaks in Fig. 2 and Fig. 3, it can be seen that the impact of digital news sentiment on housing price volatility during the sample period has not yet reached the level of traditional news sentiment. Fig. 4 shows the dynamic correlation coefficients between two different sources of news sentiment, with significant time-varying values ranging from 0.260 to 0.540 , indicating that the correlations between traditional news sentiment and digital news sentiment varies to a moderate extent.

Although there is a certain correlation between them, they are not completely synchronized. Digital news often has higher immediacy and diversity, while traditional news may focus more on deep analysis and long-term impact, so the two may differ in sentiment expression. In addition, we noticed that the correlation coefficients decreased in the later stage of the sample period, indicating that in the current diversified media ecology, the difference in the focus of market interpretation between the two kinds of media has increased, leading to a slight weakening of their sentiment correlation.

Overall, there has been a moderate positive correlation between news sentiment from both sources over the long term, with a slight decrease after 2019. Before 2019, the positive correlation between traditional news and housing price volatility was significantly greater than that between digital news and housing price volatility, which is related to the high credibility of traditional news over the long term. However, after 2019, the correlation direction between the two types of news sentiment and housing price volatility is no longer consistent. Traditional news sentiment is generally negatively correlated with housing price volatility, while digital news sentiment remains positively correlated with housing price volatility. We believe that there are two possible reasons. On the one hand, the media industry ecosystem is undergoing a huge transformation, and on the other hand, the differentiation of the focus of news reporting between the two types of media is becoming increasingly apparent.

3.2. Empirical Analysis Based on TVP-SV-VAR Model

The DCC-GARCH model can effectively characterize the dynamic correlation between variables. Although the correlation can change over time. However, it assumes that the correlation between variables is symmetrical and the variation of correlation is limited by the fixed structure preset by the model, lacking flexibility. In contrast, the time-varying parameters of the TVP-SV-VAR model allow for more flexible changes in the correlations between variables, enabling it to cope with the evolution of more complex market structures and dependencies. Additionally, the TVP-SV-VAR model can also examine the asymmetry of bidirectional correlations between variables.

3.2.1. Selection of the Lag Order

The selection of the lag order is based on the Information Criteria, as shown in Table 2, where * represents the optimal lag order under a certain criterion. It can be seen that when the lag order is 1, the FPE, AIC, SIC, and HQIC values are the smallest.

3.2.2. Model Estimation

Following Nakajima [34], the estimation method of the model adopts Markov Chain Monte Carlo (MCMC) algorithm [36]. This paper sets the model lag period to 1, MCMC sampling to 10000 times, and discards the first 1000 pre burn values to obtain the posterior distribution of model parameters.

Table 3 and Fig. 5 show the results of the model estimation. The model parameter estimation results in Table 3

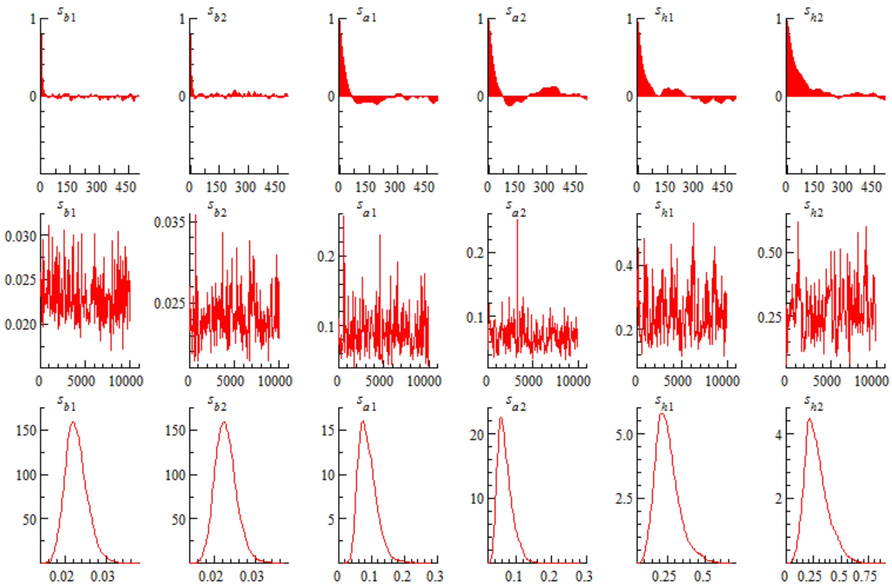

Fig. 5. Parameter diagram in MCMC simulation.

Table 2. Selection of model optimal lag order under different criteria

Lag	FPE	AIC	SIC	HQIC
0	0.0233	4.756	4.820	4.782
1	0.0070*	3.562*	3.819*	3.666*
2	0.0071	3.569	4.018	3.751

show that the posterior mean of each model parameter is within the 95% confidence interval.

The Geweke test statistics are all below the critical value of 1.96 at the 5% confidence level, therefore the null hypothesis of a posterior distribution is accepted at the 5% confidence level. The small Inefficiency Factors indicate that the MCMC sampling frequency is effective, and further effective posterior inference can be made. This paper uses the MCMC algorithm to estimate the model parameters effectively. Fig. 5 contains the autocorrelation coefficients, simulation paths, and posterior distributions of the samples. It is not difficult to see that after removing the samples within pre burning period, the autocorrelation coefficients converge, indicating that the sample selection method can effectively generate uncorrelated samples. In summary, the MCMC simulation results are effective.

3.2.3. Impulse Response Analysis in Different Lag Periods

Fig. 6 shows the impulse response formed by one unit of standard positive shock at 1, 4, 8, and 12 periods in advance, respectively. We can observe that the three variables have the greatest response to their own impact, with varying degrees of decrease in response intensity over time. Traditional news sentiment has the greatest decrease, followed by housing price volatility, while the decrease in digital news sentiment is the least significant. This indicates that all of these variables have obvious characteristics of developing according to their own inertia. Especially due to the decline of traditional news, that characteristic of it has become increasingly less apparent in recent years. In addition, the response of the three variables to their own shocks is strongest when lagged by 1 period, and the response intensity becomes weaker as the lag period becomes longer.

By observing the interactive relationship between news sentiment from two different sources, we found that traditional news sentiment and digital news sentiment influence each other. When subjected to a unit standard positive impact from the traditional news, the digital news response is positive, and vice versa. However, in terms of response values, the impact of traditional news on digital news is much greater. Therefore, although there is a two-way feedback mechanism between the two, it is evident that traditional news has a greater impact. In addition, the pulse response curves with different lag periods have similar trends, and the response intensity decreases over time, which is also related to the current development dilemma of traditional media.

The interactive relationship between traditional news sentiment and housing price volatility shows significant

Table 3. . Estimation results of TVP-SV-VAR model.

Parameter	Mean	SD	95%U	95%L	Geweke	Inefficiency Factor
sb1	0.0228	0.0026	0.0183	0.0285	0.104	7.02
sb2	0.0229	0.0026	0.0184	0.0285	0.558	10.94
sa1	0.0888	0.0280	0.0483	0.1535	0.658	25.98
sa2	0.0696	0.0219	0.0398	0.1185	0.168	34.97
sh1	0.2492	0.0771	0.1300	0.4394	0.382	59.66
sh2	0.2764	0.1026	0.1194	0.5171	0.164	90.01

temporal variability. When subjected to a positive impact of one unit standard of traditional news sentiment, the response of housing price volatility is positive, and the response curve generally shows a downward trend over time. The two peaks occurred during the relaxation period of China's real estate regulation policies (2014-2016), and the response intensity significantly decreased after 2017. Similarly, the response intensity varies under different lag orders, with larger response values in lag periods 1 and 4, indicating that the impact of traditional news on housing price volatility is short-term. On the other hand, traditional news sentiment is also affected by housing price volatility. Although it was negative in the early years and positive in recent years, the impact is much smaller in response values than the impact of traditional news sentiment on housing price volatility.

The number of digital news is increasing year by year, and the audience is becoming more and more extensive. However, from Fig. 6, we found that the impact of digital news sentiment on housing price volatility is relatively low and has obvious temporal variability. Before 2017, the response lagged by 4 periods, and after 2017, the response was stronger in the first period, indicating that the immediacy of the impact of digital news on housing price volatility is becoming increasingly apparent. The significant decrease in response intensity after 2019 may be due to the impact of COVID-19. On the other hand, the sentiment of digital news is also affected by housing price volatility, with a greater response intensity after 2017.

Overall, the interaction between the three variables is generally positive. Except for a few time points, the influence of traditional news sentiment on the other two variables has significantly decreased since 2017, which is related to the gradual decline of traditional media after 2017. However, due to the long-standing credibility of traditional media among the public, its impact on the other two variables is relatively high, indicating that although its development has faced difficulties in recent years, its influence cannot be ignored. In addition, the interaction between variables is mainly based on short-term effects.

3.2.4. Impulse Response Analysis at Different Time Points

In addition to pulse response analysis under different lag periods, the TVP-SV-VAR model also supports pulse response analysis at different time points, as shown in Fig. 7. The three time points selected in this paper are October 2011, January 2016, and October 2021, corresponding to the early, middle, and late stages of the sample period, respectively. It should be noted that the number of traditional news reports in the late stage of the sample period has greatly decreased compared to the early and middle stages. The reason is that the development of traditional media has been in a difficult situation due to the impact of digital media, especially since 2017, much traditional media has announced the suspension of publication every year. In addition, October 2021 was also during the COVID-19 pandemic.

By observing the interactive impulse response among news sentiment from two different sources and housing price volatility, we found that: (1) From the perspective of the intensity of impulse response, most of the interactive relationships between the three variables are mainly manifested as short-term effects, with peak values within a lag of around 3 months. After the peak values, the response intensities become weaker as the lag period increases. The only exception is the $\varepsilon_{DNS} \uparrow \rightarrow HPV$, which has a peak value happening around 5 month later than the impulse in October 2011, the early stage. At that time, the influence of digital news sentiment is still weak. (2) As expected, the three variables have similar response to their own impact at different time points, with varying degrees of decrease in response intensity over time. This indicates that all of these variables have obvious characteristics of developing according to their own inertia. Comparing the decrease of impulse response, it can be seen that the decrease of impulse response on the three variables in October 2021 is the fastest. To some extent, both people and market under the pressure of the epidemic are fickle. In fact, news sentiment from two different sources in January 2016 has faster decrease than those in October 2011, while the case of housing price volatility is a little opposite, which indicates

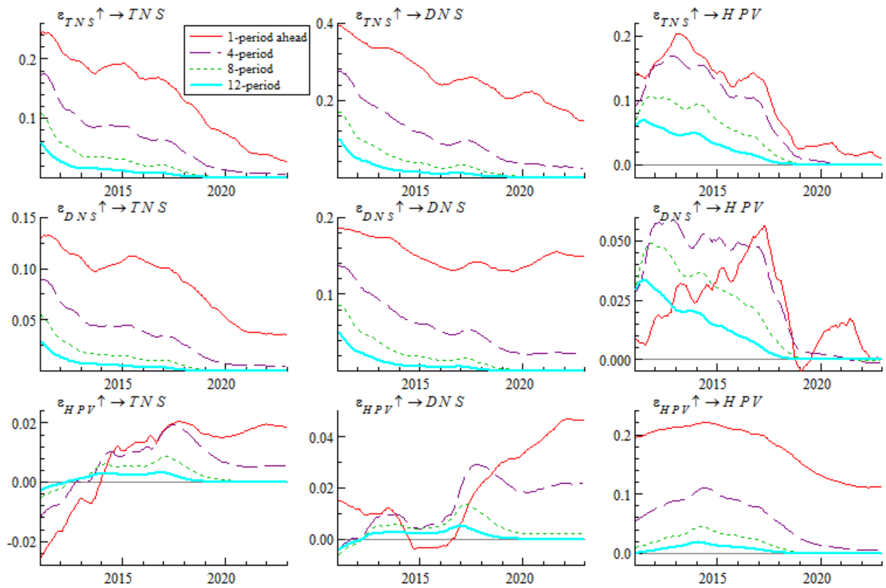

Fig. 6. Impulse response diagram in different lag periods.

that the fickleness phenomenon is developed over time and expanded from news sentiment to housing price volatility. (3) Observing the impulse response plots in the first row of Fig. 7, we found that the impact of traditional news sentiment on the other two variables in the early stage of the sample period is greater than that in the middle stage, and further greater than that in the late stage. This is one more evidence of the weakened influence in the development issues of the traditional media industry after 2017. (4) The impulse response plots in the second row of Fig. 7 show the impact of digital news sentiment. Similarly, the impact of digital news sentiment on traditional news sentiment is weakened among the early, middle, and late stages, which may be from the development issues of the traditional media industry after 2017. We focus on observing the influence of digital news sentiment on housing price volatility. At the early and middle stages of the sample period, the response curve of housing price volatility is unstable within a lag of 4 periods due to the positive impact of one unit standard of digital news sentiment. It reaches its peaks at lag 3 and 4 periods, respectively, and the lag decreases. In contrast, the response curve in the late stage of the sample period reaches its peak in the current period and then decreases. This indicates that the impact of digital news sentiment on housing price volatility is becoming increasingly immediate. (5) The impulse response plots in the third row of Fig. 7 shows the impact of housing price volatility. It can be seen that the impact of housing price volatility on traditional news sentiment was negative in October 2011 and positive in January 2016 and October 2021, but the response intensity was not significant. The impact of housing price volatility on digital news sentiment is positive at all three time points, and the effect is significantly greater in the late stage of the sample period than those in the early and middle stages of the sample period. That indicates the difference of attentiveness between traditional news sentiment and digital news sentiment on housing price volatility. Overall, news sentiment is also subject to reverse feedback from housing price volatility, especially in the late stages of the sample period when digital news sentiment is more sensitive to housing price volatility.

3.3. Empirical Analysis of Volatility Spillover

Diebold and Yilmaz [37] proposed the DY Spillover Index, which is based on the decomposition of the forecast-error variance of the VAR model, to measure the spillover effects among different variables. Subsequently, Diebold and Yilmaz [35] improved this method by adopting a generalized variance decomposition framework, making the forecast-error variance decomposition invariant to the ordering of variables. Following Diebold and Yilmaz [35], this paper applies the Spillover Index model to estimate the information transfer effect between traditional news sentiment, digital news sentiment, and housing price volatility. Table 4 presents the total static volatility spillover based on a first-order VAR model (see Table 2) and generalized variance decompositions of 10-month-ahead forecast errors. The row "Contribution to others" represents the total spillover

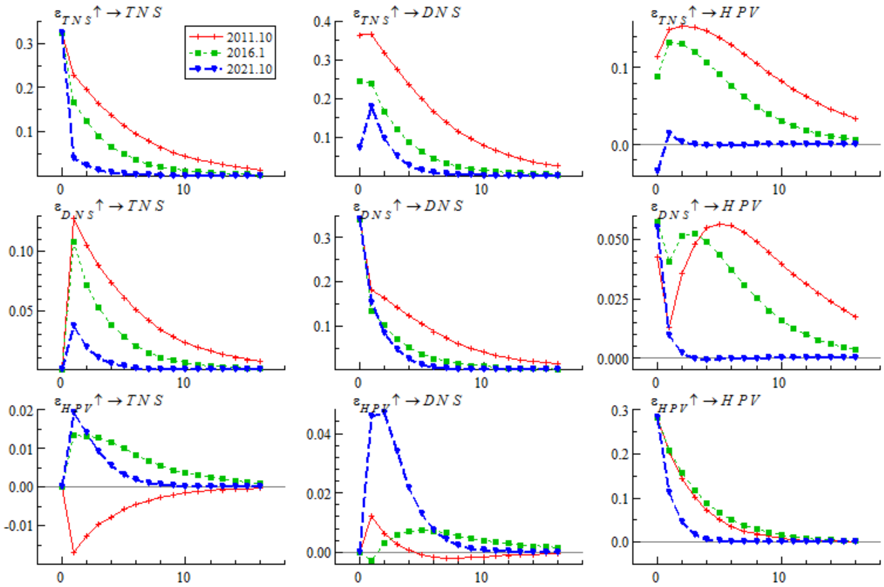

Fig. 7. Impulse response diagram at different time points.

from one variable to other variables, and the column "From others" represents the total spillover from other variables to one certain variable. The row "NET" represents the net spillover from one certain variable to other variables, which is "Contribution to others" minus "From others". Note that the intersection point of the row "Contribution to others" and the column "From others" is meaningless. Instead, "TCI" means "Total Connectedness Index", which is usually used as the index of the total spillover, and its value is 40.4.

Table 4. Static Spillover Index

Variable	TNS	DNS	HPV	From others
TNS	54.8	36.1	9.1	45.2
DNS	33.4	57.8	8.8	42.2
HPV	17.6	16.1	66.3	33.7
Contribution to others	51.1	52.3	17.8	TCI
Net	5.9	10.1	-15.9	40.4

Observing Table 4, we draw the following conclusions: (1) The total spillover effect between variables is not low, with an average total spillover effect of 40.4% between TNS, DNS, and HPV, indicating significant information transmission and mutual influence among these three variables. (2) The self variable overflow is higher than the cross variable overflow. The self variable overflow index of HPV is 66.3%, while TNS and DNS are 54.8% and 57.8%, respectively. (3) The external spillover effects of each variable and the degree to which they are affected by the external spillover effects of other variables vary. The total spillover contribution of TNS to other variables is 51.1%, the external spillover effect of other variables is 45.2%, and its net spillover effect is 5.9%. The total overflow contribution of DNS to other variables is 52.3%, the external overflow effect of other variables is 42.2%, and its net overflow effect is 10.1%. The total spillover contribution of HPV to other variables is 17.8%, the external spillover effect of other variables is 33.7%, and its net spillover effect is -15.9%. It is evident that HPV is more affected by spillover effects from other variables, while its own spillover effects on other variables are relatively small. (4) Overall, the spillover effect of TNS on HPV is slightly greater than that of DNS on HPV, which is consistent with the conclusions of the previous two models.

3.4. Discussion of the Results

The empirical analysis results of this paper are summarized as follows. Firstly, the interaction between the three variables is mainly manifested as short-term effects, and the impulse response diagrams show that their interaction has significant temporal variability, exhibiting different dynamic characteristics at different time periods. Secondly, all three variables have obvious characteristics of developing according to their own inertia, and the spillover effect of self variables is higher than that of cross variables. Thirdly, due to the impact of the development of digital media, the drawbacks of traditional media have gradually become apparent, leading to a weakening of its influence after 2017. We found that the influence of traditional news sentiment on other variables in the early stage of the sample period was greater than that in the middle stage, and further greater than that in the late stage. Fourthly, there is a significant positive correlation between news sentiment from two different sources. Additionally, housing price volatility is more strongly influenced by the spillover effects of these two types of news sentiment, while their spillover effects on other variables are relatively small. Fifthly, before 2019, both types of news sentiment had a positive impact on housing price volatility, with traditional news sentiment having a greater influence and dominating the market. However, after 2019, the impact of traditional news and digital news on housing price volatility has diverged, with traditional news sentiment being negatively correlated with housing price volatility, while digital news sentiment remains positively correlated. We believe that there are various reasons. On the one hand, the media industry ecosystem is undergoing a huge transformation, and the influence of traditional news is weakening. On the other hand, the differentiation in the focus of news reporting between the two types of media is becoming increasingly apparent. Traditional news focuses on interpreting government policies, which are relatively stable and conservative, while digital news pays more attention to market dynamics and reflects market trends in a timely manner. Sixthly, although the traditional media industry has faced difficulties in recent years, the spillover effect of traditional news sentiment on housing price volatility is slightly greater than that of digital news sentiment throughout the entire sample period. Therefore, the influence of traditional media cannot be ignored.

3.5. Policy Suggestions

This paper proposes the following policy recommendations regarding the dynamic correlation between news sentiment and housing price volatility. Firstly, policy makers should pay attention to the transmission effects of news sentiment on housing price volatility. With the increasing role of digital news in influencing housing price volatility, policy makers should particularly strengthen the supervision of digital news content, establish news verification and content monitoring mechanisms, timely identify and handle false or misleading information, and avoid the excessive impact of exaggerated or misleading news sentiment on the market. In addition, although the amount of news released by traditional media is limited, its influence cannot be ignored due to its strong credibility and authority, ensuring the transparency and objectivity of reports related to the real estate market. Secondly, in response to the spillover effects of news sentiment, the government can adopt more proactive public opinion guidance strategies. Especially during periods of significant volatility in the real estate market, the government should promptly release authoritative information to stabilize market sentiment, and encourage economic experts and media from different sources to objectively interpret market changes and enhance information transparency at the same time.

4. Conclusions

With the diversified development of news media, the impact of news sentiment on the real estate market has become increasingly complex. Traditional news sentiment and digital news sentiment, as two different sources of sentiment, may have significant differences in the mechanism and intensity of influencing housing price volatility. Traditional news has strong authority, relative stability, and conservatism, while digital news tends to report hot events in a timely manner, and may even present sentiment and preferences, but its credibility is relatively poor. This paper systematically examines the dynamic correlation and spillover effects between the sentiment of two different sources of news and housing price volatility from a heterogeneity perspective, using three empirical analysis methods. The evaluation indicator of dynamic correlation is the correlation coefficient, and the spillover effects are evaluated on the basis of DY Spillover Index. Moreover, the value $\varepsilon_A \uparrow\rightarrow B$ ($A, B \in \{TNS, DNS, HPV\}$) is also used to evaluate the levels of impulse response among the three variables.

Future research can make improvements and extensions in the following areas. Firstly, consider introducing a wider range of data sources to capture more diverse media sentiment, especially in the context of widespread dissemination on self media and social media, which may have a more direct and rapid impact on housing price volatility. Secondly, further refine the classification of news sentiment and differentiate the differential impacts of different types of news contents (such as policy news and economic news) on housing price volatility. Finally, explore the heterogeneity effects in different regions, especially considering the differences in market conditions. The spillover effect of news sentiment on housing price volatility may have regional specificity, which will provide a basis for more refined policy formulation.

5. References

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