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Provincial Linkage Characteristics of Hog Price in China Based on Linkage Social Network Analysis Method

Jiyun Bai, Northeast Agricultural University, Harbin, China
Muyan Liu, College of Engineering, Northeast Agricultural University, Harbin, China
Li Ma, College of Engineering, Northeast Agricultural University, Harbin, China
Jun Meng, College of Arts and Sciences, Northeast Agricultural University, Harbin, China

ABSTRACT

In order to obtain the visual data of linkage structure and network characteristics of hog price among provinces in China, an improved analysis method of social network correlation was proposed in this article. The lift of association rules were introduced to analyze the correlation of hog prices in different provinces in China and taken as the weight matrix of network analysis. Besides, based on social network analysis parameters and UCINET visualization technology, network analysis was carried out on the linkage relation and linkage characteristics. The application results show that, the lift of association rules can quantitatively and precisely obtain the correlation and differences of tendency of hog price, and the established network structure and parameters can visually and quantitatively present the linkage characteristics of hog price among regions and provinces.

KEYWORDS

Lift of Association Rules, Linkage Analysis, Network Analysis

INTRODUCTION

China is the world's largest producer and consumer of pork, and the production and circulation of hog has a crucial impact on people's daily life. However, due to restrictions in environment and industrial policies, hog price fluctuation presents significant regional differences, and the range and causes of fluctuation in hog prices in different regions are significantly different (Zuo, Cai, & Tan, 2016; Chen, et al.,2011). Meanwhile, with the deepening coordinated development of regional economy and reduced costs in commodity circulation, price fluctuation in different regions is not isolated, but presents linkage characteristics in space to some extent (Sun, Zong & Qiao, 2016; Liu & Pang, 2018). What kind of provincial linkage in hog price and how can we simulate the network structure of provincial price linkage to help our nation formulate regional regulation and control policies have become questions worth discussion.

At present, the conduction analysis on the fluctuation of hog price in China is mainly focused on the conduction between upper and lower reaches in price fluctuation, and time series method

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is adopted in most researches, such as Johansen Cointegration Test, Granger causality Test, finite distributed lag model, VEC model for linear relation study on price conduction (Dong, Xu, Li, & Li,2011; Jia, Yang, & Qin,2013). Other scholars adopted asymmetric error correction models (Mensah-Bonsu et al., 2011; Bhardwaj et al., 2012) and threshold autoregressive models (Rezitis & Reziti, 2011; Acquah, 2012) on the linear relation in price conduction of pork industry chain and its price conduction characteristics are also asymmetric (Pan & Li, 2015; Wang, 2017). However, there are few studies on the characteristics of horizontal conduction of hog price. The research results by Tian (2010) showed that, the hog price in China was mainly conducted from producing area to sales area. Wang (2017) applied synchronous coefficient to measure the regional coordination in hog price fluctuation and found that, fluctuations in hog prices showed strong co-movement among provinces and regions. The emerging producing areas in live pig market take the lead in price fluctuation, main sales areas and main producing areas are the price-affected parties (Wang, Wang, & Li, 2018).

These conclusions fully demonstrated the regional differences in hog price fluctuation in China and the linkage among price regions. However, the studies still need to be improved in the following aspects: firstly, current studies have discussed the similarities in hog prices among provinces, they are mainly qualitative analysis; secondly, the price linkage characteristics among different provinces have not been discussed in current studies. For the multiple provinces with complex relationship, the overall characteristics of hog price linkage network have not been studied. To this end, taking hog price as the research object and by introducing the social network analysis integrated with association rules, the linkage strength, linkage network structure in hog price fluctuation as well as the position and function of provinces in the linkage were discussed. Also, based on the results were visualized based on UCINET method to obtain visualized and precise characteristics of hog prices among provinces in China. Social Network Analysis (SNA) is a complex systematic discipline and quantitative methodology. It can offer the transmission process of various relationships within a group, and explain the formation of the group structure. It was initially widely used in medical policy network measurement (Valente, 2016; Nima, 2018; Başak, 2018). Recently, SNA has been recognized and used in more fields. For example, Teresa et al. assessed the intersectoral knowledge on understanding, intensity and structure in the Timor-Leste mental health system Used by using the quantitative SNA (Teresa et al., 2019); I-Cheng analyzed the co-occurrence of two pollution events at the monitoring station under two severe PM2.5 pollution conditions and their spatial correlation characteristics with bd-based SNA and data visualization analysis tool (I-Cheng, 2019). In this paper, SNA was introduced to discuss the hog price linkage network structure among provinces, and the network structure characteristics were discussed quantitatively by analyzing various parameters in the SNA. In SNA, obtaining the initial weight matrix of the network analysis is the starting point and the key point. To this end, lift of association rules (Lee, 2017; Chen, 2017) was introduced to obtain the linkage weight between any two provinces. Thus, data mining and data visualization were closely integrated to achieve quantitative and visual analysis of hog price structure among different provinces and regions.

The structure of this paper is as follows: Section 2.1 introduced the data collection and pre-processing method of this paper, section 2.2 introduced the linkage social network analysis method and analyzed the parameters of the association rule, and introduced the lift parameter; then introduced social network analysis method and visualization technology, and finished program design and usage specification through Python language, UCINET and NetDraw. Section 3 calculated and analyzed the results of upgrading degree of association rules and network structure of provinces. Section 4 drew a conclusion on this paper.

MATERIALS AND METHODS

Data Acquisition and Preprocessing

According to province layout in China, except for special regions such as Taiwan and Tibet Autonomous Region, the three-breed hog prices in other 30 provinces and municipalities were investigated. Sample data from March 23, 2016 to March 23, 2019 were selected. The data were from statistical yearbooks, the Internet, statistics issued by government departments and related enterprises, such as http://www.zhuwang.cc, http://www.yz88.cn, http://www.roujiaosuo.com. The data mining preprocessing technology was used for data processing, and a database of 30×1096 dimensions was constructed.

Model Methods

1. Linkage social network analysis and visualization technology analysis:

    a. Linkage social network analysis.

Social network analysis sets the research object as points. It obtains the network structure by introducing the initial weight matrix, and analyzes the network structure characteristics through parameter analysis. The initial weight matrix can set the distance and similarity between any points according to different research questions. In order to explore the hog price linkage network structure among different provinces and regions, in this paper, lift between any two provinces was taken as the element in the weight matrix to obtain a more precise network structure.

    b. Introduction of association rule algorithm and parameter analysis.

Association rule algorithm is also called association mining algorithm, which searches the frequency mode, linkage, correlation and cause-effect structure among item sets or object sets in transaction data, relation data and other information carriers (Ruiz, Gómez-Romero, & Molina-Solana, 2017). Association rule is constrained by both parameter support and confidence. When the support of the data item set A is greater than the given minimum support degree, A is called a frequent item set.

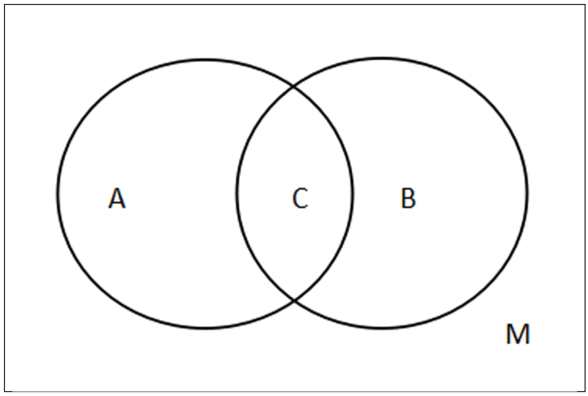
        i. Support

Support refers to frequency of the rule, which is the probability that the item set {A, B} appears at the same time. In Figure 1, M represents the population, the two circles A and B represent two item sets, and C represents the intersection part between A and B. Then the support is the ratio of C to M in Figure 1, and the calculation formula is:

$$support\left(A \Rightarrow B\right) = P\left(A \cap B\right) = num\left(A \cap B\right) / \, num\left(M\right)$$

$num\left(\cdot\right)$ represents the number of transaction sets that contain a specified set of items. For example, in the event of hog price, M contains hog price of all dates observed of each province. A contains the dates of increase of hog price in Heilongjiang province, B contains the dates of the increase of hog price in Inner Mongolia, and C represents the same dates of increase of hog price in both provinces. Support refers to the ratio of C to M, that is, the ratio of dates in which the hog price in two provinces increased simultaneously to the total number of observed days. The value can express the frequency of co-occurrences of the increase of hog price in both provinces.

Figure 1. Parameter analysis of association rules



ii. Confidence

Confidence refers to the intensity of a rule, which is the probability that B appears when A appears, that is, the ratio of C to A in Figure 1, and its calculation formula is:

$$confidence\left(A \Rightarrow B\right) = P\left(B \mid A\right) = num\left(A \cap B\right) / \, num\left(A\right)$$

In the event of hog price, for example, confidence indicates ratio of the number of days with rising prices of both provinces to that of one of the two provinces, it can also present the probability that the price of the province B would rise when that of province A increases.

c. Improvement of association rule parameter.

Support and confidence are two standard parameters in association rule algorithm, however, they cannot solve the problems in a comprehensive way. For example, the confidence of A to B is greater than the confidence of A to C, but it does not mean that the dependence of B on A is greater than the dependence of C on A. It is also related to the proportion of B and C in the population. When the ratio of B is higher than C, it is natural that the confidence of A to B may be greater than the confidence of A to C, but it does not fully reflect the true relationship between the two events, we still need to abandon the effect of proportions in the calculation. Thus, lift was introduced as follows:

$$lift\left(A \Rightarrow B\right) = \frac{P\left(B \mid A\right)}{P\left(B\right)} = confidence\left(A \Rightarrow B\right) / \, support\left(B\right)$$

According to the above formula, it can be known that $lift\left(A \Rightarrow B\right)$ represents the quotient of A's $confidence\left(A \Rightarrow B\right)$ and support degree of B $support\left(B\right)$. $support\left(B\right)$ indicates the proportion of B in all data. $confidence\left(A \Rightarrow B\right)$ is discussed on this denominator, with the aim to avoid the impact of the proportion of B in all data. According to the formula of confidence, $confidence\left(A \Rightarrow B\right)$ is only related to the proportion of A in the population, but not to the proportion of B in the population. When the data B is relatively small in the population, even if all the emerged data are in the same period as A, a large result of $confidence\left(A \Rightarrow B\right)$ cannot be obtained, and when data B accounts for a large proportion in the population, it is easy to obtain a large $confidence\left(A \Rightarrow B\right)$. Obviously, such a $confidence\left(A \Rightarrow B\right)$ is not general.

This formula can be also interpreted as follows: let the ratio of the intersection part C to A be divided by the ratio of B to M, that is to say, comparing the proportion with characteristics of B in A and the proportion with B characteristics in the population, if the result is greater than 1, then the proportion with B characteristics in A is stronger and takes up over the mean value of the population; if the result is less than 1, it indicates that the proportion with B characteristics in A is weaker and takes up less than the mean value of the population. Lift reflects the comprehensive correlation between A and B in association rule, the higher the lift is and lift>1, the higher the positive correlation would be; the lower the lift is and lift<1, the higher the negative correlation would be. If lift=1, then there is no correlation between A and B. On the basis of basic association rule, lift was introduced to obtain effective association rule.

d. Process of Apriori data mining algorithm in association rule.

Apriori algorithm (Chen, Xie, & Shang, 2017) is a classical algorithm in association rule. It mainly includes two steps: The first step is to retrieve all the frequent item sets in the transaction database by counting, pruning, and concatenating the data sample attributes one by one, that is, the item sets whose support is no lower than the minimum support set by the user; the second step is to construct a rule that satisfies the minimum confidence of the user by applying the frequent item set, thereby finally get the lift. The process is listed below:

i. Pandas toolkit in Python was used in this paper to introduce price variation after conversion to record data, then the recorded data of price variation are stored in a list and zero values are removed. The initial frequent itemSets was established;
ii. Initialize support and lift, set the minimum support value to 0, and runs in a loop calling the recorded data in the list itemSets to get the support between any two provinces. Save the support between provinces to the initialized support in support_select in the form of dictionary;
iii. Using the calculated support data and some part of the process in the Apriori algorithm, lift data between provinces can be further calculated, then call the support data in the dictionary within names of provinces to obtain the lift data of any two provinces after segmentation. Set the degree of lift data to 1 for a province itself, and save them in the initialized data dictionary promote_select and output in the form of dictionary.

The hog price in 30 provinces of China are converted into recorded data of price variation, which are further divided into recorded data of rising and falling prices. A total of 1095 lines represent records of hog price variation in the latest three years, and each column represents a province. A total of 30 columns are the 30 provinces of China. After importing matrix into python and removing zero values, the recorded data of price variation was stored in the form of a list, then retrieve the recorded data by the Apriori algorithm to realize the association rule of price variation among provinces and obtain support, confidence and lift of provinces. Through understanding the concepts of the three parameters, the lift data of the provinces were selected to construct the weight matrix. Table 1 shows part of lift data of Anhui province.

e. Parameter introduction of Social network analysis.

Table 1. Part of lift data of Anhui province

A	B	$lift\left(A \Rightarrow B\right)$
Anhui	Yunnan	0.6791
Anhui	Inner Mongolia	1.5037
Anhui	Peking	1.3157
Anhui	Jilin	1.6620
Anhui	Sichuan	1.3157
Anhui	Tianjin	1.4736
Anhui	Shandong	2.2157
Anhui	Shanxi	1.4354
Anhui	Guang dong	1.3246
Anhui	Guang xi	1.4354
Anhui	Xinjiang	1.5390
Anhui	Jiangsu	2.1345
Anhui	Jiangxi	1.8796
Anhui	Hebei	1.7543
Anhui	Henan	1.8148
Anhui	Zhejiang	1.8125
Anhui	Hunan	1.4170
Anhui	Hubei	1.5647

Based on lift weight data of the provinces, the hog price network structure of the provinces can be constructed and analyzed. The common social network analysis parameters include:

i. Network density

Network density refers to the tightness of connection between each point in a figure. In this paper, it is an important factor that embodies the network density of hog prices. Suppose the hog network has N nodes with actual relation number of L, then network density is:

$$D = \frac{L}{N \times (N-1)}$$

The value of network density is between 0-1. The higher the network density is, the closer of the relation between each province in the hog price network is, otherwise the relation between provinces would be looser.

ii. Centrality parameters

Centrality parameters generally include three categories, one is the degree centrality: it represents the tightness level of connection between a node and other nodes in the network; the second is the between centrality, which is the intensity of the behavioral subject's control over resources. If a node has a relatively higher between centrality, it means it has higher ability of controlling other nodes. The third category is closeness centrality, which is defined by the closeness between different behavioral subjects in the network. If the closeness centrality of one node is very high, then this node does not have to send information through too many other nodes.

iii. Core-peripheral analysis

According to the size of the central parameters of the individuals in the network, which the number of individuals that can be contacted, the more important or active individuals in the network are identified. These individuals are the core of the network and has a greater impact on the whole network. Other individuals are the peripheral part of the network.

f. Procedures of social network analysis and visualization.

UCINET (University of California at Irvine NETwork) is a very strong software for social network analysis, which is also a Windows program driven by menu and a most commonly used program for comprehensively analyzing social network data and other similar data (Xie, et al.,2018). This program itself doesn't include graphics programs for network visualization, but it can output data and results to software such as NetDraw, Pajek, Mage, and KrackPlot for drawing. The UCINET-based social network analysis has the following procedures:

i. Binarization processing

The matrix analyzed by UCINET must be binarized, and the binarization operation instruction is Transform.Dichotomize. In this study, the lifting weight matrix obtained in the association rule was binarized, and the threshold value selected here is the network density of the weight matrix, and the binary matrix of lift was obtained, as is shown in Table 2.

ii. Density analysis

The operation instruction of the software is Network.Cohesion.Density.Old Density procedure, which can obtain the overall network density of the matrix. The processed binary matrix was input into UCINET for density analysis, and the network density of the linkage matrix among provinces is 1.439, which reflects the overall level of lift in the matrix, so it can be considered that the relationship between provinces is very strong when the degree of lift is greater than this value.

iii. Centrality visualization and parameter analysis

The operation instruction of the software is Analysis.Centrality Measures, which can draw the connection diagram between the networks, and can be improved according to research direction, so that the connection between the networks can be clearly expressed. The operation instruction of degree centrality is Network.Centrality and Power._Degree(legacy), which is to measure the transaction ability of actor in the network. The operation instruction of Between Centrality is Network.Centrality and Power.Freeman Betweenness.Node Betweenness. Between Centrality studies the extent to which an actor is between the other two actors and thus is an index for control ability. The operation instruction

Table 2. Binary matrix of linkage between provinces

	Anhui	Peking	Fujian	Gansu	Guang dong	Guang xi	Guizhou	Hainan	Hebei	Henan	Heilongjiang	Hubei	Hunan	Jilin
Anhui	0	1	1	1	1	1	0	0	1	1	0	1	1	1
Peking	1	0	1	1	1	1	0	0	1	0	0	1	1	1
Fujian	1	0	0	1	1	0	1	0	0	0	1	0	1	0
Gansu	0	0	0	0	0	1	0	0	0	0	0	1	1	0
Guangdong	0	1	1	0	0	1	0	0	1	0	0	0	1	1
Guangxi	1	1	0	1	1	0	1	1	1	1	0	0	1	1
Guizhou	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hainan	0	0	0	0	0	1	0	0	0	0	1	0	1	1
Hebei	1	1	1	0	1	0	0	0	0	0	0	0	1	0
Henan	1	0	0	0	0	0	0	0	0	0	0	1	1	1
Heilongjiang	0	1	1	1	0	0	0	1	0	0	0	0	0	0
Hubei	1	1	0	1	0	0	0	0	1	1	0	0	1	1
Hunan	1	1	1	1	1	1	1	1	1	1	0	1	0	1
Jilin	1	1	1	1	0	1	0	1	1	1	0	0	1	0

of closeness centrality is Network.Centrality and Power.Closeness measure. It studies the extent to which an actor is not regulated by other actors.

2. Construction and analysis of hog price linkage network

The provincial linkage analysis of hog price based on association rule algorithm and social network analysis technology has the following steps:

a. Calculate the support of variation of hog price and set the minimum support as 0, then obtain the support data of any province;
b. Calculate lift between any provinces using the obtained support and price change records, construct a weight matrix of the linkage relationship, and the weight of its own linkage is 1;
c. Input the weight matrix of the degree of lift into the social network analysis software and calculate the network density for binarization processing;
d. Analyze the core position and centrality index of network nodes and map the network between provinces;
e. Consider the rationality of linkage according to the size and geographical location of the linkage matrix and exclude unreasonable factors to obtain the final linkage relationship between the provinces.

RESULTS AND DISCUSSION

1. Result analysis of the Lift of Hog Price Association Rules.

At the end of executing the association rule algorithm, the support and confidence data are used to obtain the lift of price linkage between provinces. The lift data obtained by the Apriori algorithm shows that the synchronous price lift between provinces ranges from 0.44 to 5, with mean value of 1.54. The linkage province pairs with higher lift can be obtained, as is shown in Table 3.

It can be inferred from Table 3 that, when the lift of two provinces is greater than 1, the price change in one of the provinces would promote that of the other province. It can be concluded from the direction of geographica position and transportation of provinces that, the transportation and influence direction of hog is from central cities to peripheral provinces. There is an evident region division of western, northeastern and southeastern regions, and there are also regional spillovers to some extent.

Table 3. Province pairs with higher lift

Province1	Province2	Lift	Province1	Province2	Lift
Henan	Shandong	2.3327	Henan	Hebei	2.8945
Hunan	Guangdong	2.2814	Hunan	Hubei	2.2417
Hubei	Shandong	2.1989	Hubei	Hebei	1.9391
Sichuan	Chongqing	2.1075	Sichuan	Guizhou	2.1087
Hebei	Shandong	1.9577	Hebei	Tianjin	1.8432
Anhui	Shandong	2.2157	Shandong	Liaoning	2.3611
Jiangxi	Anhui	2.2734	Jiangxi	Shandong	2.2989
Yunnan	Guangxi	1.9872	Shanxi	Jiangsu	2.1301
Anhui	Jiangsu	2.1345	Guangdong	Hainan	1.9848
Liaoning	Hebei	2.0039	Guangdong	Guangxi	2.1285
Hebei	Shanxi	1.9740	Hubei	Anhui	1.9341

2. Network Result Analysis of Hog Price:

    a. Visualization analysis of network structure.

Figure 2 shows the visualization results of centrality, and the block size of nodes of provinces represents degree centrality of each province.

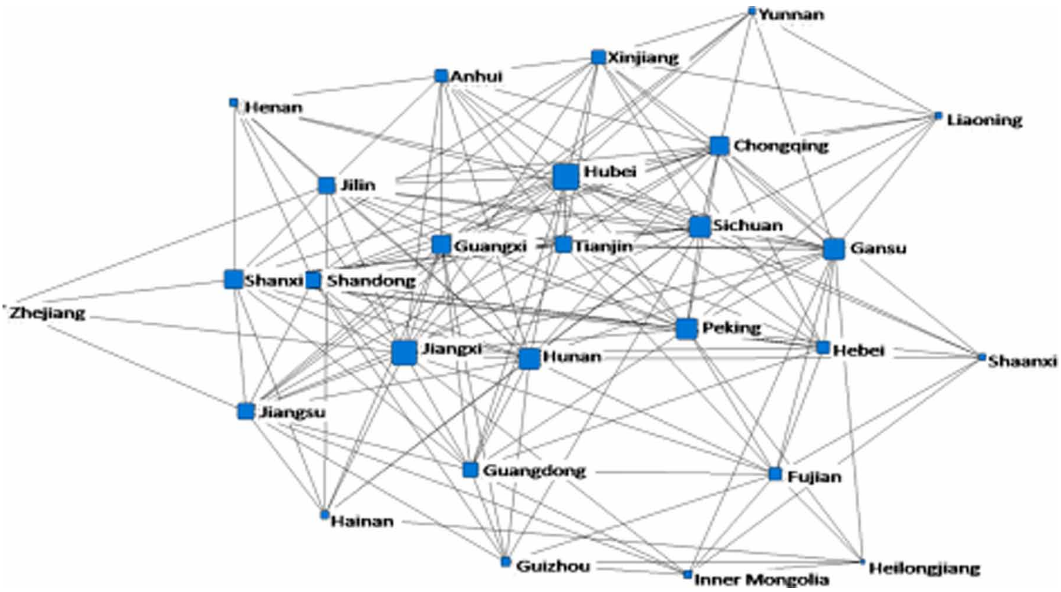
It can be seen from Figure 2 that, provinces like Hubei, Jiangxi, Beijing, Hunan and Sichuan have higher degree centrality, and Jiangxi, Hunan and Sichuan have higher hog output and may transport hog to other provinces; Beijing with higher economic position may receive and sell hog that cannot be totally consumed by peripheral provinces, so Beijing has many contacts with other provinces.

    b. Centrality parameter analysis.

Table 4 shows the three kinds of centrality values in the linkage matrix network between provinces.

It can be inferred from Table 4 that, the degree centrality and closeness centrality of provincial nodes are basically opposite. The fewer provinces are associated with one province, the less the hog price of the province is affected, and the more stable the price would be and not easily limited by fluctuations in external prices. The between centrality and degree centrality of different provinces have the positive correlation tendency. The data in Table 4 show that, Hubei, Jiangxi, Beijing, Hunan, Sichuan and Henan have higher between centrality and higher degree centrality, the nodes with higher

Figure 2. Linkage network of provinces in China



between centrality have greater influence in local region in the network, and the values of between centrality embody the importance of the province in the network.

3. Results and Discussion:

   a. The above analysis shows that, hog price linkage characteristics demonstrate an evident network structure. The existence of the hog price network structure shows that the analysis of hog price should start from “point” to “plane”, from “one-dimension” to “multi-dimensions”, from “quantity” to “structure”;
   b. The position and population development level of each city in the network structure are correlated to some extent. It can be concluded from the results above that, cities with higher linkage centrality may have higher hog slaughter and higher population density, and population and development level determine the impact in the linkage structure. Among the first ten provinces in slaughter in 2018, it can be seen in Table 4 that the betweenness centrality and degree centrality are relatively high. Among the first ten provinces in population in 2018, the values of closeness centrality of the provinces were relatively high in Table 4. Table 5 shows the closeness between each province and population as well as hog industry development level in the network structure.
   c. The linkage of change in hog price and geographic correlation between provinces are related. The above results show that, geographically close and regional relevant provinces have strong linkage relationship. This is also due to the positive correlation between the transportation distance and the transportation cost. Distant provinces may not have much hog transportation, which may not significantly affect price change. Table 3 shows 22 pairs of provinces with strong linkage, after observing their position analysis, there are 16 pairs of adjacent provinces, as is shown in Table 6, showing the great importance of geographic position to linkage relationship.

Table 4. Centrality index of provinces in China

Province	Between Centrality	Degree Centrality	Closeness Centrality
Hubei	16.556	20	1.6
Jiangxi	21.135	19	1.65
Peking	15.216	17	1.75
Hunan	12.197	17	1.75
Sichuan	15.279	17	1.75
Henan	13.624	15	1.62
Shandong	15.85	15	1.9
Gansu	13.815	15	1.75
Guangxi	7.434	15	1.85
Shaanxi	9.948	15	1.85
Chongqing	7.08	15	1.85
Jilin	7.779	14	1.9
Jiangsu	12.767	14	1.9
Tianjin	3.964	14	1.9
Guangdong	4.924	13	1.95
Xinjiang	4.3	12	2
Anhui	6.829	11	2.05
Fujian	5.345	11	2.05
Hebei	14.728	11	2.05
Guizhou	3.654	9	2.15
Henan	2.719	8	1.2
Inner Mongolia	3.114	8	2.2
Liaoning	0.434	7	2.3
Shanxi	1.628	7	2.3
Yunnan	0.868	7	2.25
Heilongjiang	1.7	6	2.35
Zhejiang	0.111	4	2.55

d. Some pairs of provinces with strong correlations can be selected from the data of lift between provinces, as is shown in Table 3. These province pairs are mainly concentrated in the core areas of central China. For such strong linkages between provinces, in implementing macro-regulation of hog prices in the core provinces, the impact of the regulatory process on non-core provinces with strong linkages should be taken into consideration. The regulation of non-core provinces can be started from the core provinces that have strong linkage with the non-core provinces. Taking regulation on core provinces as the main means, and self-regulation as supplementary means, the degree of linkage with peripheral provinces can be checked.

Table 5. Relationship between network parameters and population and hog industry development level

	Province	Hog Slaughter	Between Centrality	Degree Centrality	Province	Populations	Closeness Centrality
1	Henan	5428.43	13.624	15	Guangdong	11169	1.95
2	Hunan	5034.29	12.197	17	Shandong	10005.83	1.9
3	Sichuan	4669.82	15.279	17	Henan	9559.13	1.62
4	Shandong	4104.36	15.85	15	Sichuan	8302	1.75
5	Hubei	3614.93	16.556	20	Jiangsu	8029.3	1.9
6	Hebei	3004.26	14.728	11	Hebei	7519.52	2.05
7	Yunnan	3003.96	0.868	7	Hunan	6860.2	1.75
8	Guangdong	3003.16	4.924	13	Anhui	6254.8	2.05
9	Guangxi	2906.71	7.434	15	Hubei	5902	1.6
10	Jiangxi	2662.50	21.135	19	Zhejiang	5657	2.55

Table 6. Position relationship of provinces in linkage

Province1	Province2	Position Relationship	Province1	Province2	Lift
Henan	Shandong	adjacent	Henan	Hebei	adjacent
Hunan	Guangdong	adjacent	Hunan	Hubei	adjacent
Hubei	Shandong	nonadjacent	Hubei	Hebei	adjacent
Sichuan	Chongqing	adjacent	Sichuan	Guizhou	adjacent
Hebei	Shandong	adjacent	Hebei	Tianjin	adjacent
Shandong	Anhui	adjacent	Shandong	Liaoning	nonadjacent
Jiangxi	Anhui	adjacent	Jiangxi	Shandong	nonadjacent
Yunnan	Guangxi	adjacent	Shanxi	Jiangsu	nonadjacent
Guangdong	Anhui	nonadjacent	Guangdong	Hainan	adjacent
Liaoning	Hebei	adjacent	Guangdong	Guangxi	adjacent
Hebei	Shanxi	adjacent	Hubei	Anhui	adjacent

CONCLUSION

Based on the panel data of Chinese hog price from March 2016 to March 2019, by introducing lift parameter in the association rule together with social network analysis method, a quantitative and qualitative analysis was made on the hog price linkage network using UCINET software and Python language in this paper. This study provided new concepts and methods for livestock product risk analysis under complicated data environment, also provided a new perspective for studying the cause of hog price fluctuation and state macro-control, aiming at offering a basis for developing control policies of differentiated regional hog price.

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Bai Jiyun was born at Heilongjiang Province, China, in 1979. She received a PhD in Control Science and Control Engineering from Harbin Institute of Technology, Harbin, China, in January 2014. She is working as an associated professor in College of Arts and Science in Northeast Agricultural University. Her current research interests include machine learning, intelligent algorithms, and smart agriculture.

Muyan Liu received her B.Admin degree in Engineering Management from the Northeast Petroleum University, China, in 2018. Currently, she is a graduate student in Management Science and Engineering from Northeast Agricultural University, China. Her research interests include agricultural data analysis.

Ma Li was born in Heilongjiang Province, China in 1976. She received a PhD in Agricultural mechanization engineering from Northeast Agricultural University, Harbin, China in January 2010. She is working as an associated professor in Engineering College in Northeast Agricultural University. Her current research interests include agricultural system engineering and industrial engineering.

Meng Jun was born in Heilongjiang Province, China in 1963. He received a PhD in Agricultural System Engineering from Northeast Agricultural University, Harbin, China, in January 2002. He is working as a professor in the College of Arts and Science in Northeast Agricultural University. His current research interests include agricultural system engineering.