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Research Article

Designing the Novel Imported Pork Producer Declaration Price Index Using Chinese Customs Import Declarations

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Pork accounts for a high proportion of the Chinese population's meat consumption, and imported pork is heavily traded, reducing supply of domestic pork in the face of continued demand. Global pork markets are becoming more competitive, riding the wind of the bilateral free trade agreement. The World Food and Agriculture Organization (FAO) compiles prices for other major food categories but does not track changes in the imported pork prices in China. This study has filled this gap by designing the Imported Pork Producer Declaration Price Index (PPI_IPD). Using the well-known Producer Price Index (PPI) model, PPI_IPD is based on the data from Chinese customs import declarations, which has high reliability and reasonableness. For this reason, the index can help governments, enterprises, analysts, and others to conduct analysis for imported pork prices in China and avoid international trade risks. The findings show that proposed PPI_IPD is highly correlated with the Chinese domestic pork market and the pork price industry stock market. The index helps monitor changes in international pork prices and is an effective tool for analyzing and controlling trade risks.

1. Introduction

China is among the world's leading pig breeders and a significant importer of pork, a bulk-traded agricultural product. According to China's National Bureau of Statistics, pork consumption accounts for more than 70% of the overall meat consumption by residents in China. In terms of demand for pork products, per capita pork consumption in China has increased by 0.16 kg per year in the past two decades. In 2007, pork consumption accounted for 65% of meat consumption in rural areas and approximately 57% in urban areas [1]. African swine fever broke out in China in late 2018 and has caused substantial loss to China's hog industry. Consequently, China's pork production was massively disrupted, resulting in the highest pork prices in history [2]. This affected the market prices of chicken meat and aquaculture products. Pork is the dominant meat in Chinese diet, and its price is a critical component of China's Consumer Price Index [3]. Making a reasonable warning on pork prices to maintain a normal supply of pork has become an imminent issue.

Pork price volatility is a key aspect of financial risk for all market stakeholders, including producers, enterprises, and consumers [4]. To reestablish the normal domestic supply of pork and stabilize pork prices, the Chinese government has been trying to increase the amount of imported pork, in addition to motivating domestic production. China's 2020 pork imports are expected to reach a record 3.7 mmt, more than double the amount of imports in 2018, which were 1.6 mmt [5]. Despite large fluctuations in pork prices in recent years, there is no scientific or objective index to measure its price changes. To analyze the trend of fluctuations in imported meat prices from a macroeconomic aspect [6], the evaluation of first-hand ex-factory meat prices is critical. It is crucial to specify a scientific and reasonable price index to study pork price fluctuations.

The price index can not only reflect the changes in the economic situation but also characterize the overall market situation, evaluate the investment performance of investors, and provide a basis for researchers to study the market. It also has a price-guiding effect on signed trade contracts [7]. The Producer Price Index (PPI) is a widely used index of how much a group of producer goods and services have changed in price over time. The U.S. Producer Price Index for prepackaged software [8] was created in 2002 to reflect price changes in the design, development, and manufacturing of computer prepackaged software. In order to track changes in the prices of seafood traded internationally and provide an early warning signal for changes in seafood prices, the Food and Agriculture Organization of the United Nations created Fish Price Index (FPI) [9] in 2012. The price index method helps to aggregate large prices and quantities of several goods or services into a scalar to understand the extent of these prices change.

Therefore, this study designs Imported Pork Producer Declaration Price Index (PPI_IPD). The PPI_IPD is designed to fill a gap in the price guidelines for imported pork in China. It can be used to measure and monitor the extent of international meat purchase and the increases and decreases in the sales prices. In summary, some contributions are described in this article as follows:

(1) This first-hand transaction information collected within four years is arranged according to the basic principles of index designing by PPI model. PPI_IPD can estimate imported pork prices in China by analyzing the price of imported pork customs declarations from China Customs. It serves as a crucial foundation for determining price changes for imported pork as well as an efficient tool for analyzing the overall trend of imported meat and managing trade risk

(2) It was discovered that the price index values suggested in the study change one month in advance and can therefore be used as a leading indicator by analyzing the correlation coefficients between PPI_IPD and domestic pork market prices and stock prices of companies involved in pork processing

(3) The experimental results demonstrate that PPI_IPD has the potential to assist in the development of trading strategies by using decision trees to create an intuitive decision model. Using PPI_IPD to create more complex trading strategies can assist businesses and customers in setting up early warning systems when dealing with a more complicated and intense trading environment

This article is structured as follows for the remainder of it. The second section largely provides an overview of the study's relevant work and provides an explanation of the experiment's methodology. The third section introduces the preprocessing method for the data and proposes the formula for calculation of PPI_IPD. The fourth part uses the PPI_IPD calculation formula proposed in this study to calculate the price index and puts forward the concept of dynamic index, sets different index selection proportions for correlation experiments and uses the decision tree algorithm to predict the trend, and draws the experimental conclusion. Finally, the fifth section summarizes the experimental results and puts forward some suggestions and shortcomings for further improvement.

2. Related Work

The design of PPI_IPD is based on an analysis of the prices of imported pork customs declarations into China, following PPI model. Therefore, the work and theory associated with the design of PPI_IPD will be described in detail in this section.

2.1. Harmonized System Involved in Import Pork Declaration. Import declarations are used by customs authorities to improve trade facilitation. Import declarations support the following functions: risk assessment of goods crossing the border, identification of illicit goods, calculation of revenue payable, and examination of permits and licenses. These functions are required to be communicated to customs and facilitate the collection of trade statistics [10]. In order to accurately identify each type of goods, the World Customs Organization has developed Harmonized System codes as a multipurpose international product terminology. The Harmonized System code is generally referred to as the HS code. The HS codes a six-digit code issued by the World Customs Organization [11]. It is applicable for taxation, statistics, production, transportation, trade control, inspection, and quarantine. Each transaction is identified by a six-digit code, arranged in a legal and logical structure, and is supported by well-defined rules to achieve uniform classification [12, 13]. At present, more than 98% of global trade volume [14] uses this catalog as a standard language for international trade. Examples of the 6-digit code are shown in Table 1.

2.2. Model of Producer Price Index. Before the Producer Price Index (PPI) was designed, Laspeyres and Paasche indexes are well-known indexes used in many countries to measure the changes in the general price levels [15]. The difference between these two indexes is the choice of weights. Laspeyres index not only solves the contradiction that the overall units of different measurement units cannot be directly added but also plays the role of weights objectively. The calculation of Laspeyres index is shown in

$$P_L = \frac{\sum p_1 q_0}{\sum p_0 q_0}. \tag{1}$$

It can be conflicting whether to use the base period or the reporting period as the weight, when calculating the weighted composite index. In 1874, the German economist and politician Paasche proposed to fix these measurement factors in the reporting period, in article *About the Price Developments Recorded by the Hamburg Stock Exchange*. Thus, it is more reasonable to implement the Paasche index. The calculation of Paasche index is shown in

$$P_P = \frac{\sum p_1 q_1}{\sum p_0 q_1}. \tag{2}$$

Table 1: Examples of Harmonized System code for commodity tariffs.

First classification	First classification name	Secondary classification	Secondary classification name	Tertiary classification	Tertiary classification name
01	Live animals	0101	Live horses, asses, mules, and hinnies	010111	Pure-breed breeding animals
				010119	Others
				010120	Asses, mules, and binnies
		…	…	…	…
02	Meat, edible meat offal	0201	Meat of bovine animals, fresh or chilled	020110	Carcasses and half-carcasses
				020120	Others cuts with bone in
				020130	Boneless
		…	…	…	…
		0203	Meat of swine, fresh, chilled, or frozen	020311	Carcasses and half-carcasses
				020312	Hams, shoulders, and cuts thereof, with bone in
				020319	Other frozen
				020321	Carcasses and half-carcasses
				020322	Hams, shoulders, and cuts thereof, with bone in
				020329	Other
		…	…	…	…
…	…	…	…	…	…

From the Laspeyres index, the weight of Laspeyres index is based on the basis weight (p_0) in formula (1). However, there is a defect in this index because the actual calculation cannot reflect structural changes [16]. The use of fixed weights not only tends to cause errors and revisions in real index and prices when base periods are updated, but the errors themselves are biased [17]. Subsequently, if the sample structure changes (whether the sample size or the sample ratio changes), the index cannot reflect the change in the index value brought about by this change. To solve this problem, the Chain Laspeyres index is introduced. The calculation of Chain Laspeyres index is shown in

$$L_t = \left[\sum W_{t-1} \frac{P_t}{P_{t-1}} \right] L_{t-1}. \quad (3)$$

The Chain Laspeyres index is based on the Laspeyres index, which updates the weights and geometric averages of the low-level classification indexes every year. The Laspeyres index calculates the reporting period index on a fixed base ratio. However, the Chain Laspeyres index is adjusted to first calculate the ring index, then synthesize the fixed base index, and synthesize the fixed base through the ring ratio form. These methods can solve the structure change. Owing to calculation error, the Chain Laspeyres index is more accurate in reflecting the trend of price changes. It is a commonly used method in statistical offices in national and international organizations worldwide, such as the FAO and the National Institute of Statistics and Economic Studies in France (INSEE) [18].

The PPI is released monthly by the National Bureau of Statistics of China and is compiled using the Chain Laspeyres index. According to formula (3), price changes of individual commodities are given different weights in the calculation of the PPI depending on their importance. These weights reflect the share of the corresponding product group in all observed commodities sold in the country. The PPI is theoretically supposed to cover producers in all industries and is therefore to measure the price fluctuations of the purchases required by producers in the production process. It is an important economic index that can be used to conduct economic analysis and decision-making and to measure the risks of price instability. In addition, the PPI can also be used to monitor market development and competition, food safety issues, inflation trends, and price inflation transmission from production levels to the retail sector.

2.3. Pearson's Correlation Coefficient. Pearson's correlation coefficient is used in the financial industry to demonstrate a relationship or correlation between the index and the object being tested. The Pearson's correlation coefficient, also known as the product moment correlation coefficient, is represented in a sample by r [19]. The calculation of correlation coefficient is shown in

$$r = \frac{\sum_{i=1}^{n} \left(X_i - \bar{X}\right)\left(Y_i - Y\right)}{\sqrt{\sum_{i=1}^{n} \left(X_i - \bar{X}\right)^2} \sqrt{\sum_{i=1}^{n} \left(Y_i - \bar{Y}\right)^2}}. \quad (4)$$

It is also based on the deviation of the two variables from their respective averages. The degree of correlation between the two variables is reflected by multiplying the two deviations. Pearson's correlation coefficient explores the strength of the correlation between two variables. According to the magnitude of the value, correlation between two variables can be judged and tested. The closer the value is to 1, the stronger the correlation between the two variables. Among them, 0.8-1.0 indicates that the correlation is extremely strong; 0.6-0.8 indicates that it is strong; 0.4-0.6 indicates moderately strong correlation; 0.2-0.4 indicates that variables are weakly related, and 0.0-0.2 signifies extremely weak or no correlation. Correlation coefficient is a statistical indicator used to reflect the close degree of correlation between variables. Similarly, when the correlation coefficient of the two financial time series increases, the correlation also becomes stronger.

2.4. Decision Tree. Decision trees, also known as classification trees, are one of the widely used algorithms in expert systems. They are used to capture knowledge [20] owing to their ability to model time-series data and easily capture nonlinear trends and relationships between indicators. They are also extremely easy to interpret. Additionally, decision tree techniques have been shown to be interpretable, efficient, problem-independent, and capable of handling large-scale applications. The decision tree models highlight the individual relationships associated with classes and the combinatorial associations of features associated with decision classes. The structure of a decision tree is shown in Figure 1.

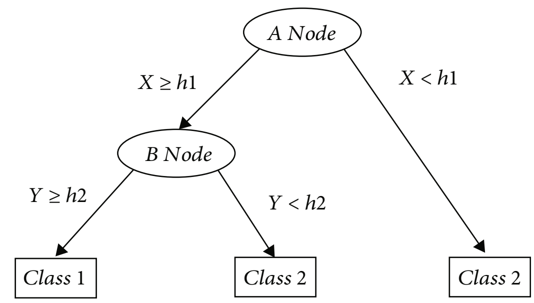

FIGURE 1: Schematic drawing of a decision tree, with the node and class.

This method classifies a population into branch-like segments that construct an inverted tree with a root node, internal nodes, and leaf nodes [21]. The leaf nodes (class) represent the classification result, and the branches represent the classification rules. The process of building a decision tree generally includes the following steps. The first step is to choose an appropriate algorithm from the data samples used to build the decision tree. The standard algorithms used are ID3, C4.5 [22], CART, etc. The second step is to prune the decision tree. The third step is to extract knowledge rules or perform analysis from the decision tree.

3. Proposed Imported Pork Producer Declaration Price Index

When designing a price index, it is necessary to compress the price and quantity information of many different products into one number. This continuous number represents the change in trends for a given period. For example, the well-known PPI measures the average change in the prices paid by producers for a fixed market of goods and services [23]. Indexes can measure the extent to which prices of general goods (representing broad categories such as food, housing, gasoline, and health care) have risen or fallen in an economy. Similarly, PPI_IPD is used as an indicator to measure the degree of change in the price of imported meat. To reflect price changes in a timely and correct manner, these data must be readily available and easy to update. This section starts with the selection of data involved in the design of PPI_IPD, then the most proper data preprocessing method is chosen, and the formula of PPI_IPD is designed using the formula of PPI as a prototype.

3.1. Data Source Selection. The imported pork declaration form conveys first-hand information of meat products entering the Chinese market and has fundamental guiding significance for index compilation. This article uses imported pork customs declarations data from January 2019 to April 2022 as the data source for designing the index. Data of 41,479 transactions in total were provided by international freight forwarding company. In the transaction data, the label name includes the date of the order, HS code, CIP code, country, label product name, product name, license name, weight, unit price, currency, commodity type, total amount, and customs exchange rate. The HS code is used for distinguishing meat products.

However, unlike the six-digit coding system of the international HS code introduced in Chapter 2, China's imports and exports use a ten-digit code, where the first six digits are equivalent to the HS code, and the last four digits are subheadings [24]. It is based on HS classification principles and methods and is an extended two-digit code based on the actual conditions of import and export commodities.

This article selects 6 representatives imported pork from China customs declarations to design PPI_IPD. The names of imported meat products and their HS codes are shown in Table 2. In this table, it shows the names of the main imported pork parts in China and their corresponding ten-place HS codes on the customs declaration form.

3.2. Data Processing and Cleaning. Data processing and cleaning compensate for the lack of information in the imported pork declaration form data set. In the process of transaction or information entry, the data may not be updated on time or the human operation may be improper, which will cause the transaction data to be messy and missing. Lack of attribute values is often reported and considered inevitable [25]. To overcome the above problems, this study treat the collected data to reduce errors and improve the data [26].

There are many reasons for missing data, and the missing data may contain critical information. Therefore, this data must be filled according to the information that the missing value contained under different application scenarios. For ease of description, this subsection defines the types of missing label values.

Labels with complete values, this data is called normal data. In the index compilation process, the labels that have the highest impact value are transaction weight, unit price (RMB), and total transaction amount. The lack of such data

Table 2: Imported pork part name and corresponding HS code.

Names of parts of imported pork	HS code
Fresh or cold bone-in pig front legs, hind legs, and their meat	0203120090
Other fresh or frozen pork	0203190090
Other frozen whole and half pork	0203219090
Frozen bone-in pig front legs, hind legs, and meat pieces	0203220090
Other frozen pork	0203290090
Whole or cut other pork large intestine and bladder	0504009000

is called necessary missing data. The labels that have no influence in the index calculation process include the importing country, label product name, order product name, and license name. Such data are called unnecessary missing data. This article selects the customs declaration form price from January 2019 to April 2022 as the research period, which lasts for 34 consecutive months, with a total of 519,509 labels, of which the number of normal labels accounts for 99.8%. Nonessential, missing data accounted for only 0.17% of the overall data, while necessary missing data only accounted for 0.006%. Details of the data proportion can be seen in Table 3.

There are three main solutions for handling abnormal data: no processing, deletion of missing data, and completion of missing data. Not processing abnormal data signifies that when the missing data is nonessential, the missing label will not affect the objectivity and correctness of index compilation. Thus, data corresponding to this label is ignored.

To delete missing data is to delete data that has problems or is missing to obtain a complete dataset. This processing method greatly reduces the workload of processing abnormal data and is more effective when the proportion of abnormal data is small. However, when abnormal data is large, this method will discard a large amount of hidden information. When the original data set is small, deleting sizeable data will severely affect the objectivity of index compilation and the correctness of the results. Therefore, when the proportion of missing data is large, wrong conclusions can be drawn.

Missing data complementation refers to filling in a missing label according to the distribution of the value of the initial data set. There are several ways of complementing commonly used in data mining:

(i) Manual fill up: when the amount of data is small, it is filled by manual observation. However, this method is time-consuming and includes subjectivity. When the data is large and there are many empty values, manual filling is not feasible

(ii) Filling in data according to previous records: the missing data is filled upwards. If the price of the imported pork part i on the day t is missing, the price on day $t-1$ is used to fill the missing data, until the original data reappears. This method can make up for the missing continuous data. However, in index compilations, such calculations may cause the result to change insignificantly

Table 3: Statistics of data names and proportions from dataset.

Name	Count	Proportion
Normal data	518586	0.998223
Unnecessary missing data	899	0.001711
Necessary missing data	34	0.000065
Total	519509	1

(iii) Filling in the data with averages: the attributes in the initial data set are divided into numerical attributes, and nonnumerical attributes are processed separately. If the null value is numeric, the missing attribute is filled in according to the value based on the average value of the attribute in all other objects [27]

(iv) Completion of data using same-source meat products in the same period: data on the same meat products for the same period and transaction date in the international market is used to fill in the missing data and the transaction information for the same importing country. This way, the data source is reasonable. However, the international market data is often incomplete. If the data loss is large, the workload of data cleaning is large. The main reason for designing PPI_IPD in this study is to reflect the price of pork imported through Chinese customs, that is, the price of imported pork entering Chinese customs, rather than mastering the price changes of international pork trading malls. Although the import prices on customs declarations are correlated with the international pork market, there is a lag in the relationship. Therefore, completion of data using same-source meat products cannot be used to represent the declared prices of imported pork and the true data of entry into the Chinese market

Based on the given information, this study can delete missing values to clear the data and smooth noise data [28]. This meth can efficiently reflect the sampling variability [29]. In terms of the necessary missing data, for example, missing unit prices, or missing transaction weights, this study chooses to delete this record. This study chooses to delete the necessary missing data because its proportion is relatively small, and the proportion of all customs declaration records is supplemented by 0.1%. Even if the method of filling by average values is selected, the overall effect will not be significant.

3.3. Formula and Calculation. After processing the imported pork transaction data, this section will design the formula and calculation of PPI_IPD. Formula (5) is designed as the formula for the PPI IPD using the prototype of formula (3).

$$\mathrm{PPI}_{\mathrm{IPD}_t} = \left[\sum W_{t-1,i} \frac{P_{t,i}}{P_{t-1,i}}\right] \times \mathrm{PPI}_{\mathrm{IPD}_{t-1}}. \tag{5}$$

PPI_IPD_t is PPI_IPD value of this month. PPI_IPD_{t-1} is the index value for the previous month. $W_{i,t-1}$ represents the weight proportion of part i in $t-1$ month. $P_{t,i}$ is the average price of pork product i in the current period, and $P_{t-1,i}$ is the average price of pork product i in the previous period.

The monthly average price $P_{t,i}$ of part i of imported pork is calculated based on the price of all customs declarations and the total transaction weight of the the current month. Concurrently, the meat products are classified according to the HS code and the calculation in

$$P_{t,i} = \frac{\sum \text{price}_{t,i} \times \text{weight}_{t,i}}{\sum \text{weight}_{t,i}}. \tag{6}$$

In the formula, $P_{t,i}$ represents the average price of imported pork products i in month t. And $\text{price}_{t,i}$ represents the daily customs declaration price of imported pork products i. And $\text{weight}_{t,i}$ represents the daily imported weight of pork products i. The pork price index is calculated monthly, according to the total import amount based on the daily import declaration price and import weight. It is then divided by the total import weight of meat products i for the month, and the average price of meat part i is obtained. Taking imported meat with HS code 0203220090 as an example, the average price $P_{t,i}$ for this products from January 2019 to April 2022 is shown in Table 4.

The advantage of PPI is in the compilation of the index as it introduces weights. By doing so, it serves as a measure of the extent to which price changes in different parts of imported pork market affect the composite price. In the compilation method used in this study, the volume of imports is chosen as the weight for the weighted average. The weights are crucial in compiling the index and help conduct the calculation of the weighted prices. The weight of the pork import products i in month t is equal to the weight of imports divided by the total weight of imports in the month. It is calculated in

$$W_{t,i} = \frac{\text{weight}_{t,i}}{\sum \text{weight}_t}. \tag{7}$$

In the formula, $W_{t,i}$ represents the weight of pork import product i in month t, and $weight_{t,i}$ represents the import weight of the pork product i in month t. And $\sum \text{weight}_t$ represents the total weight of all imported pork in this month t. The changes in monthly weights obtained by HS code classification, from January 2019 to April 2022, are calculated for the import products with HS code 0203230090 as an example. The details are shown in Table 5.

Because the price index is a relative number, before calculating the PPI_IPD, a time is first chosen as a baseline, calling it the base period. The base period is the starting point for estimating index calculation. The base period is set following certain principles and considerations, taking into account its impact on the index once it is complied. For the analysis, the base date of the index is set to January 2019, the earliest date in the data on imported pork declarations, and the base point can be set to 100, based on our price index compilation method [30]. According to the above steps, this study can calculate the PPI_IPD changes in Figure 2.

Table 4: Imported pork parts 0203220090 average price ($P_{t,i}$).

Time (t)	Average price	Time (t)	Average price
2019/01	10.7034	2020/09	21.3766
2019/02	11.7682	2020/10	19.3852
2019/03	12.4383	2020/11	16.7752
2019/04	13.4886	2020/12	16.1291
2019/05	11.6292	2021/01	17.3355
2019/06	12.5624	2021/02	16.6281
2019/07	14.2692	2021/03	18.5207
2019/08	13.0059	2021/04	18.9492
2019/09	14.1144	2021/05	17.6773
2019/10	19.2061	2021/06	13.5961
2019/11	16.054	2021/07	12.4861
2019/12	15.3156	2021/08	11.6832
2020/01	14.5185	2021/09	12.4607
2020/02	16.636	2021/10	12.855
2020/03	17.319	2021/11	11.575
2020/04	15.2441	2021/12	13.254
2020/05	13.0819	2022/01	12.443
2020/06	16.4168	2022/02	6.818
2020/07	15.4445	2022/03	11.262
2020/08	17.3392	2022/04	8.737

Table 5: Imported pork parts 0203230090 transaction weight ($W_{t,i}$).

Time (t)	$W_{t,i}$	Time (t)	$W_{t,i}$
2019/01	0.9111496	2020/09	0.798534
2019/02	0.9065415	2020/10	0.740949
2019/03	0.9555526	2020/11	0.688777
2019/04	0.926783	2020/12	0.660153
2019/05	0.9542886	2021/01	0.766275
2019/06	0.9788642	2021/02	0.805948
2019/07	0.9243057	2021/03	0.811565
2019/08	0.9555342	2021/04	0.863401
2019/09	0.9589912	2021/05	0.849840
2019/10	0.9442695	2021/06	0.718746
2019/11	0.9763333	2021/07	0.726471
2019/12	0.9627879	2021/08	0.671882
2020/01	0.9426463	2021/09	0.0.9131
2020/02	0.9173355	2021/10	0.678000
2020/03	0.9444803	2021/11	0.771000
2020/04	0.9701716	2021/12	0.671024
2020/05	0.9486581	2022/01	0.790050
2020/06	0.870483	2022/02	0.910300
2020/07	0.812672	2022/03	1.000000
2020/08	0.786899	2022/04	1.000000

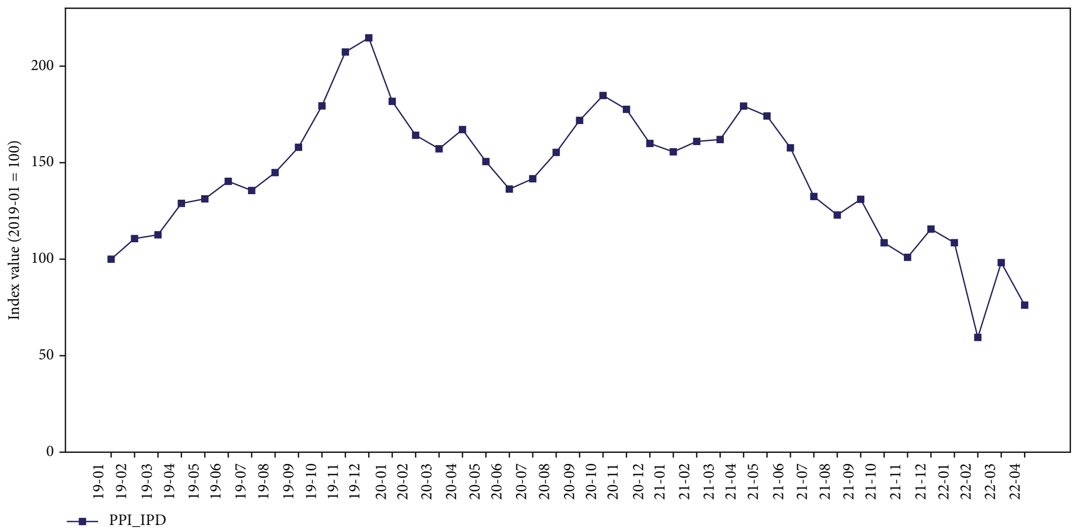

Figure 2: The PPI_IPD calculated by using formula (5).

4. Imported Pork Producer Declaration Price Index Dynamic Evaluation

This article uses trend analysis and quantitative analysis to verify the price index. Trend analysis is used to study PPI_IPD and reflect the trend chart of the field. The quantitative analysis is conducted to calculate the correlation between the two curves; calculate the correlation coefficient through the three angles of synchronization, advance, and lag; and verify the maximum correlation of the imported pork price index to the target trend. The manifestation of correlation is called linkage (also known as synchronization). Since there is a certain linkage between the two transactions, the Pearson's correlation coefficient can be used to measure it. In an open international market environment, imported pork primarily enters consumer markets, such as pork trading markets, restaurants, schools, and food processing companies. Next, this study proposes the concept of dynamic adjustment and calculates the correlation between dynamic adjusted PPI_IPD and pork market price, as well as the correlation between PPI_IPD and pork-related industry stocks, so as to prove that PPI_IPD can guide the trend of these two financial indicators.

4.1. Dynamic Adjustment Structure of PPI_IPD. To enrich and improve the imported pork price index system and provide a new underlying index for the growing indexing investments, this study introduce the dynamic index. This index is verified to maintain better sensitivity and benchmarking by adding an access threshold to the imported pork products participating in the index compilation. The PPI_IPD dynamic index uses the parent index as the sample space and sets prices based on the park market using pork-related industries' sensitivity as evaluation criteria. In the customs declaration data of imported pork for 40 consecutive months from 2019 to 2022, this study calculate the proportion of each imported pork product by calculating transaction weight and transaction amount in Table 6.

In the above table, the weights are divided by the transaction weight and the transaction amount, indicating the proportion of transactions in the imported pork parts with different HS codes. The proportion of imported pork parts with HS codes 0203120090, 0203190090, 0203219090, and 0504009000 for only four years is also relatively low, all less than 1%, compared to the proportion of imported pork parts with HS codes 0203220090 and 0203290090, which is relatively high. Thus, the minimum weights of the products in the index compilation in this study are set at 10% and 20%. Because the dynamic index does not set fixed calculation items, a specific imported pork part is deemed eligible to participate in the index calculation once its transaction weight surpasses the minimum weight requirement. Given the minimum weight of 10%, the indexing process is conducted by selecting the HS codes 0203220090 and 0203290090 for compilation. The generated index sequence is labeled PPI_IPD_10. Given the minimum weight of 20%, the indexing process is conducted by selecting the HS code 0203290090 for compilation. The generated index sequence is labeled PPI_IPD_20. Next, this study empirically validate the two dynamic indexes to determine the indicator with highest correlation and replace all the indicators originally involved in the compilation.

4.1.1. Correlation between Dynamic PPI_IPD and Market Price. Imported pork has a great price advantage over locally raised pigs, with a price ratio of 1 : 2.7. As the amount of domestic pork production decreased, the amount of imported pork increased. Imported pork has lowered the price level of the domestic pork market, and imported pork has become crucial to fill the current domestic pork supply gap. It has played an important role in suppressing meat prices in the domestic market. To verify whether the imported pork price index can reflect the changes in the domestic pork market, this study selects the market price of pork for each month from 2019 to 2022 to explore the relationship between the pork price index and market price.

Table 6: Proportion of transaction weight of imported pork parts.

Method of calculating proportion	0203120090	0203190090	0203219090	0203220090	0203290090	0504009000
By weight	0.0021%	0.0231%	0.1811%	18.0701%	81.1270%	0.5966%
By amount	0.0030%	0.0374%	0.1761%	16.3382%	83.0560%	0.3893%

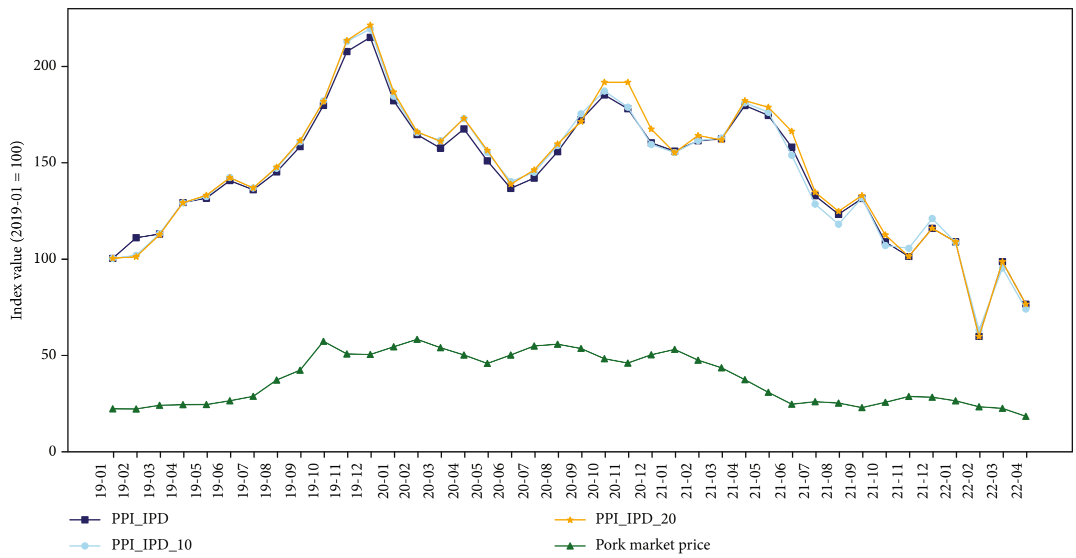

Figure 3: Three indexes' change and market price.

Table 7: Correlation coefficients of PPI_IPD and market prices in different dimensions.

Time dimension	Two months in advance	One month in advance	Synchronization	One-month lag	Two-month lag
PPI IPD	0.67414	0.66292	0.72394	0.73974	0.69646
PPI IPD	10 0.68669	0.67052	0.72742	0.74818	0.70950
PPI IPD	20 0.68464	0.66813	0.72118	0.74101	0.70598

The data [31] are released from the National Bureau of Statistics (NBS) and can reflect the changes in domestic market prices in the marketplace during the period.

This study gets two new indexes based on the two minimum trading volumes: PPI_IPD_10 and PPI_IPD_20. By comparing the market prices and parent indexes PPI_IPD, PPI_IPD_10, and PPI_IPD_20, this study plotted the trend of the three indexes with the market price. The trend of the three curves shows that all indexes have a high correlation in Figure 3.

This shows that all three index changes can cause changes in market price trends, but it is not possible to reflect which index effect is the best.

So, to prove numerically which of the dynamic index is the best, the correlation coefficients are calculated in Table 7.

Using months as the calculation period, the correlation decreases if the PP_IIPD is advanced by one or two periods. When the index lags by two cycles, the correlation coefficient decreases most significantly, by around 6.4%. But when the PPI_IPD lags by one to two cycles, the correlation correlation improves, and the correlation is highest at the one-month lag. It shows that when PPI_IDD leads the market price change by about one month, the response to domestic pork market price is higher. After the above analysis of the correlation between the index and the domestic pork market price, we can infer that the change of PPI_IPD is ahead of the market price change. When imported pork enters the customs, it can flow into the market about a month later. This also shows that PPI_IPD can be used as a leading indicator [32] to reflect the overall situation of the pork market.

Table 8: Stock name and corresponding symbol.

Name	Symbol
DELICIOUS shares price	DSP
New Hope group shares price	NSP
Muyuan Foods shares price	MSP
Shuanghui group shares price	SSP

4.1.2. Correlation between Dynamic PPI_IPD and Pork-Related Companies. In general, the more adequate the factors of production, the lower the factor costs for enterprises; the cost of production is also lower [33]. Therefore, the production cost of downstream enterprises will reduce, and the

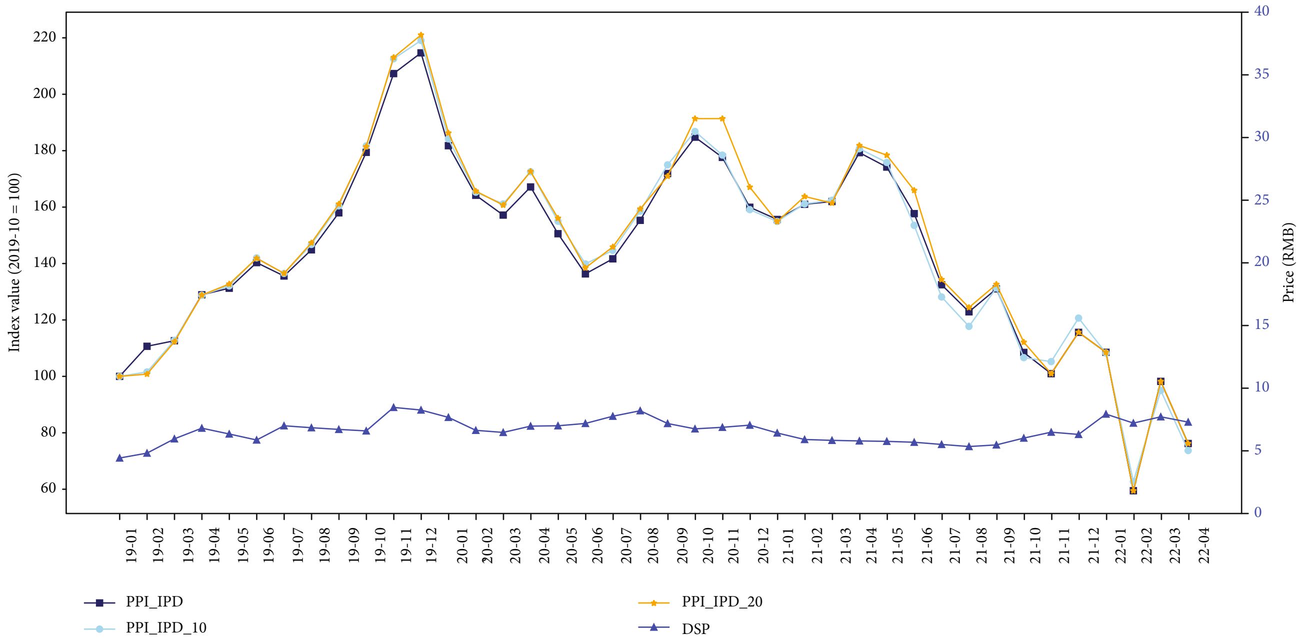

Figure 4: DSP movement versus three dynamic indexes.

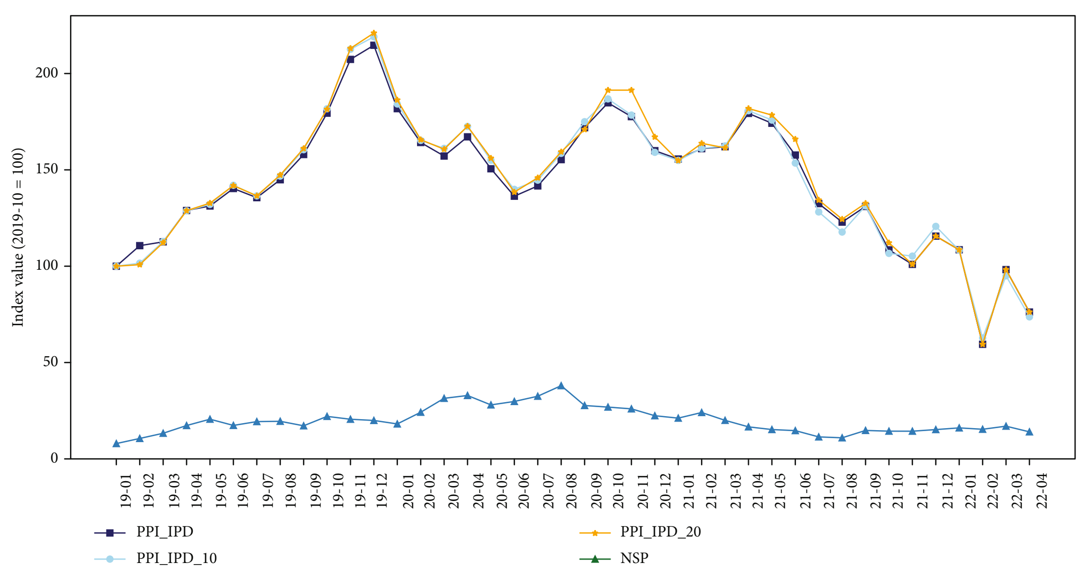

Figure 5: NSP movement versus three dynamic indexes.

market will show a prosperous trend. As raw material prices increase, the sales market continues to expand, and investor confidence improves, changing the company's share price in the short term. But as pork prices fall, the market tends to saturate, and the degree of prosperity of pork-related industries will also decline. This will lead investors and company decision-makers to reduce investment information and capital investment. In this section, stock prices of pork-related industries are selected as an index to study the degree of market boom and raw material prices. Research on correlation analysis of Chinese pork stocks has showed that Chinese pork prices have a significantly positive correlation at the 1% level. Upstream and midstream companies in the pork industry chain are more affected by changes in pork prices [34]. To verify the relevance of PPI_IPD in influencing pork-related industries, stocks with large market capital in the Chinese market meat production and processing are selected. It is considered that these sample stocks have stability and representativeness.

The purpose of PPI_IPD compilation is to reflect the changes and development of the pork enterprise, and the industries involved are extremely restrictive in nature. This study screens the sample stocks with the most industry characteristics and representativeness, which are DELICIOUS, New Hope company, Muyuan Foods, and Shuanghui group shares. The symbols used are shown in Table 8.

These four stocks are representative of all pork concept stocks in the Shenzhen Stock Exchange. Their main business

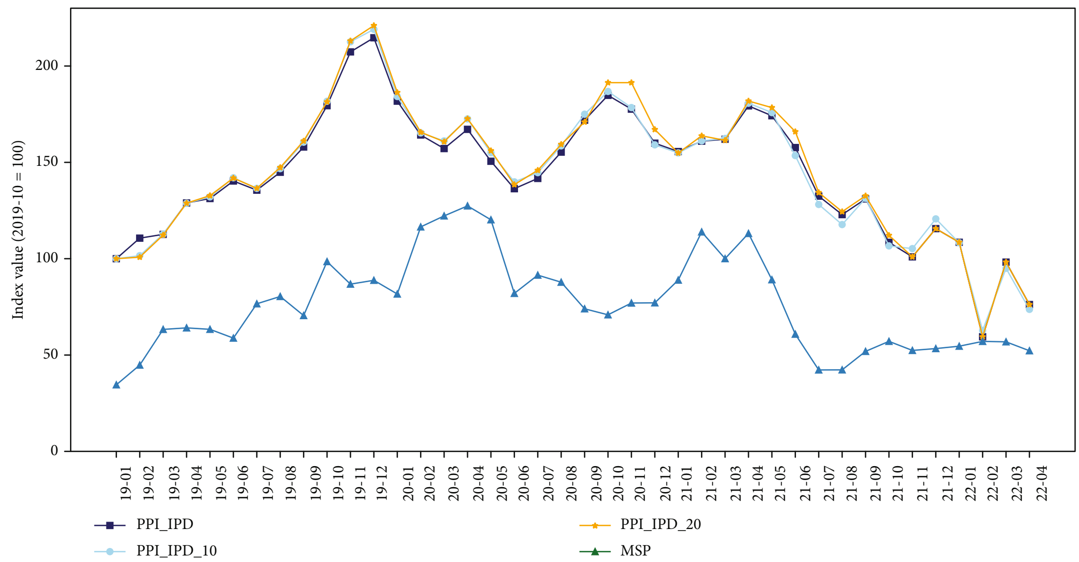

Figure 6: MSP movement versus three dynamic indexes.

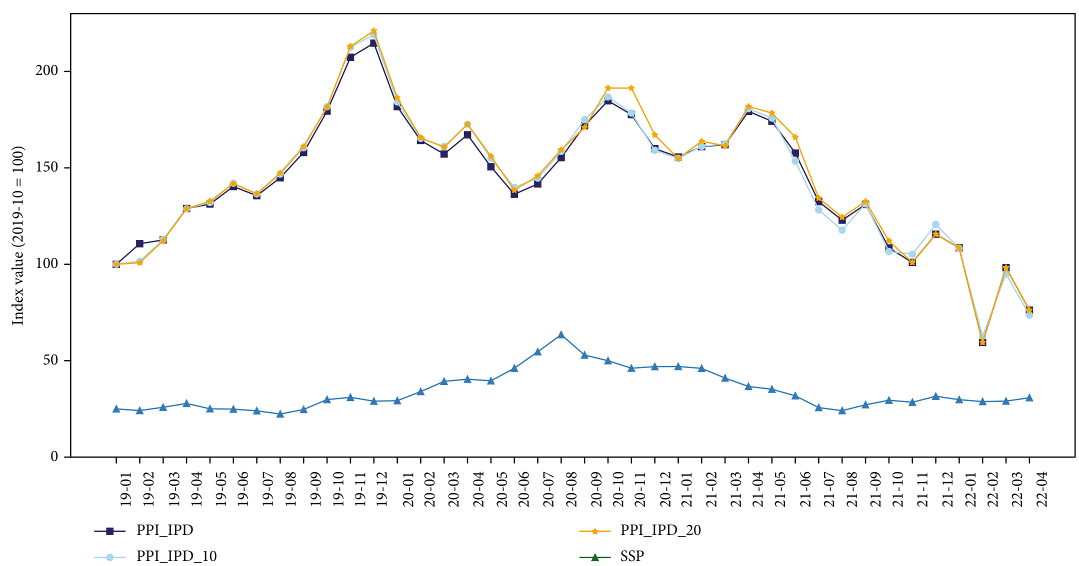

Figure 7: SSP movement versus three dynamic indexes.

Table 9: Table of correlation coefficients between dynamic index and DSP.

	Two months in advance	One month in advance	Synchronization	One-month lag	Two-month lag
PPI_IPD	-0.05600	0.14323	0.31050	0.33945	0.23169
PPI_IPD_10	-0.00450	0.19232	0.35063	0.53508	0.52192
PPI_IPD_20	-0.05886	0.15451	0.20698	0.27532	0.22809

Table 10: Table of correlation coefficients between dynamic index and NSP.

	Synchronization	Two months in advance	One month in advance	One-month lag	Two-month lag
PPI_IPD	0.33380	0.36259	0.47196	0.49918	0.49825
PPI_IPD_10	0.33380	0.39887	0.49011	0.53508	0.52192
PPI_IPD_20	0.33595	0.36836	0.48610	0.51520	0.50682

Table 11: Table of correlation coefficients between dynamic index and MSP.

	Synchronization	Two months in advance	One month in advance	One-month lag	Two-month lag
PPI_IPD	0.54077	0.56797	0.62219	0.60576	0.44415
PPI_IPD_10	0.56904	0.58600	0.64634	0.62885	0.54278
PPI_IPD_20	0.51199	0.55115	0.62967	0.61808	0.56688

Table 12: Table of correlation coefficients between dynamic index and SSP.

	Synchronization	Two months in advance	One month in advance	One-month lag	Two-month lag
PPI_IPD	0.30220	0.32325	0.37494	0.39540	0.37234
PPI_IPD_10	0.32681	0.34409	0.38872	0.39183	0.37234
PPI_IPD_20	0.32153	0.33750	0.38776	0.39067	0.38435

Table 13: Dataset of trading volume > 0% composition of the index (PPI_IPD).

PPI IPD_*t*-4	PPI IPD_*t*-3	PPI IPD_*t*-2	PPI IPD_*t*-1	Event
10.67	1.77	14.46	1.81	UpWard
1.77	14.46	1.81	6.92	DownWard
6.85	9.05	13.58	15.56	UpWard
15.56	3.54	-15.33	-9.66	DownWard
3.54	-15.33	-9.66	-4.28	UpWard
-9.66	-4.28	6.34	-9.91	DownWard
-9.46	3.91	9.63	10.68	UpWard
10.68	7.5	-3.88	-9.95	DownWard
-9.95	-2.71	3.46	0.61	UpWard
10.69	-2.86	-9.48	-15.98	DownWard
-2.86	-9.48	-15.98	-7.24	UpWard
-15.98	-7.24	6.62	-17.2	DownWard
-7.24	6.62	-17.2	-6.94	UpWard
-17.2	-6.94	14.51	-6.12	DownWard
-6.94	14.51	-6.12	-45.21	UpWard

scope involves the production, processing, and sale of low-temperature meat products, pig breeding, and feed processing, covering all aspects of pork-related industries. These activities account for 50% or more of the companies' total revenue, indicating good market growth. Excluding some factors of poor earnings, the stock rises can represent the industry ups and downs. The trading information of the sample stocks was collected from the Shenzhen Stock Exchange, and data processing and calculations were made. All stock trading data from January 2019 to April 2022 were selected for the convenience of the study, and monthly closing prices were calculated from the daily closing prices of the sample stocks. The trend changes are shown in Figures 4–7. According to the following four charts, the trends of the PPI_IPD and the four sample stocks are extremely close to each other.

Each time the rise of imported pork price index will cause the rise of DSP, NSP, MSP, and SSP trend in a period of time and maintain in one to two periods, through the trend comparison, it can show that PPI_IPD has a correlation with the four stocks, next by calculating the correlation coefficient to specify the strength of correlation between

Table 14: Dataset of trading volume > 10% composition of the index (PPI_IPD_10).

PPI IPD_*t*-4	PPI IPD_*t*-3	PPI IPD_*t*-2	PPI IPD_*t*-1	Event
1.57	11.02	14.19	2.58	UpWard
11.02	14.19	2.58	7.51	DownWard
7.51	9.35	13.23	16.99	UpWard
16.99	3.05	-15.92	-10.26	DownWard
3.05	-15.92	-10.26	-2.51	UpWard
-10.26	-2.51	7.08	-10.18	DownWard
-9.74	3.42	9.61	10.37	UpWard
10.37	6.75	-4.48	-10.84	DownWard
-10.84	-2.64	4.03	0.79	UpWard
11.25	-2.69	-12.69	-16.52	DownWard
-2.69	-12.69	-16.52	-8.14	UpWard
-16.52	-8.14	11.56	-18.79	DownWard
-8.14	11.56	-18.79	-1.32	UpWard
-18.79	-1.32	14.66	-10.27	DownWard
-1.32	14.66	-10.27	-42.08	UpWard

Table 15: Dataset of trading volume > 20% composition of the index (PPI_IPD_20).

PPI IPD_*t*-4	PPI IPD_*t*-3	PPI IPD_*t*-2	PPI IPD_*t*-1	Event
0.8	11.37	14.74	3.04	UpWard
11.37	14.74	3.04	6.87	DownWard
7.91	9.34	12.62	17.44	UpWard
17.44	3.74	-15.72	-11.06	DownWard
3.74	-15.72	-11.06	-2.99	UpWard
-11.06	-2.99	7.41	-9.61	DownWard
-11.27	5.36	9.23	7.28	UpWard
7.28	11.95	1	-12.7	DownWard
-12.7	-7.31	5.77	-1.42	UpWard
12.64	-1.89	-7	-19.04	DownWard
-1.89	-7	-19.04	-7.38	UpWard
-19.04	-7.38	6.61	-15.46	DownWard
-7.38	6.61	-15.46	-9.96	UpWard
-15.46	-9.96	14.51	-6.12	DownWard
-9.96	14.51	-6.12	-45.21	UpWard

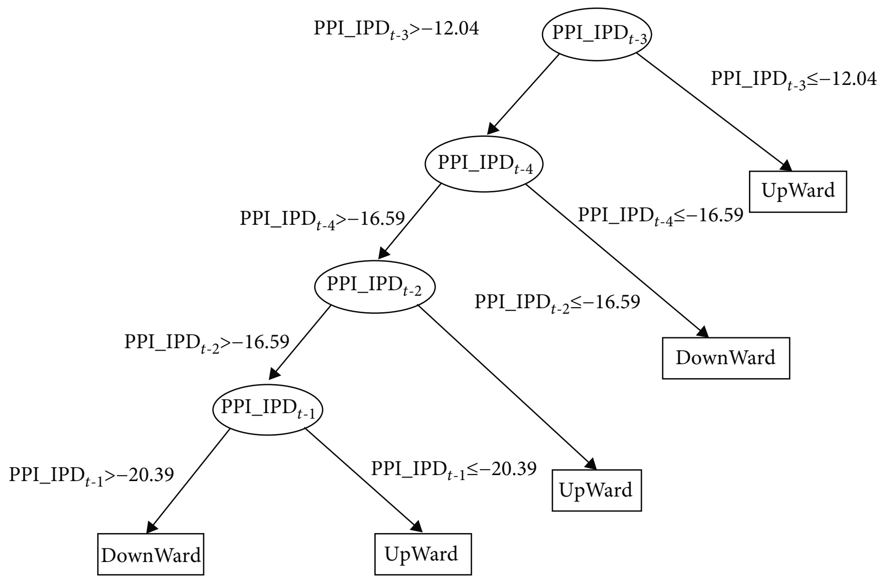

Figure 8: Decision tree formed by PPI_IPD value change.

variables; when the two curves are synchronized, the correlation is maintained in 0.3-0.6, with a moderate degree of correlation. When PPI_IPD is advanced by one or two periods, the correlation coefficient becomes smaller, and the correlation becomes worse; however, by lagging the index trend by one period, out of MSP, the correlation coefficients of all three stocks increase; i.e., the degree of correlation is enhanced, indicating that PPI_IPD is advanced with the changes of the related industries, when the price of imported pork is raised, after about one month the pass-through effect, acting in the stocks of these firms.

By calculating the correlation coefficient, as in Tables 9–12, the correlation decreases when the index is one to two periods ahead, but the correlation coefficient decreases most significantly when it is two periods behind. The correlation is best when the index is one period behind, indicating that the index is approximately one month ahead of the market price change. Across all three time dimensions, the correlation coefficients of PPI_IPD_10 are higher than those of PPI_IPD and PPI_IPD_20.

Thus, PPI_IPD_10 is ideal for explaining the boom in pork-related enterprises. That is, when the sample products are inserted in the index calculation, it is best to set the trading volume greater than 10%.

4.2. Index-Generated Decision Tree in Investment. Leading indicator is the first to change before the overall economic trend is recession or growth. It can predict the inflection point of the economic cycle, estimate the fluctuation range of economic activities, and speculate the trend of economic fluctuations. In today's society, the use of financial index for investment and wealth management has become the mainstream of contemporary era. Investment wealth management refers to the rational arrangement of funds by investors using funds to achieve the purpose of adding value and preserving value, accelerating asset growth and avoiding trade risks [35]. In this section, validating PPI_IPD allows scientists and designers to construct their investment scenarios easily and intuitively [36]. This study designs a simple decision tree model to provide analysts and investors with basic decision-making solutions to demonstrate the decision guidance of PPI_IPD. In order to make the improved indicators have better positive guiding significance as leading indicators, this study uses decision trees to model three dynamically generated price indexes.

This study defines two events: upward rebound event, UpWard, and downward rebound event, DownWard. UpWard event represents the minimum extreme point of PPI_IPD, after a period of decline, and it is about to rebound, in the trend chart, such as "∧." The DownWard event represents the situation where the PPI_IPD is about to decline after a period of increase, reaching the maximum extreme point, which resembles "∨" on the chart. The purpose of our experiment is to discern the rules of the price index reversal events, UpWard and DownWard. In other words, this study studies the characteristics of the price index in the first four months, when the events Upward and DownWard appear.

This study defines the composition of the data set to use the index growth rate of the PPI_IPD for the previous four months, which are PPI_IPD_t-4, PPI_IPD_t-3, PPI_IPD_t-2, and PPI_IPD_t-1. The goal of the current study is to mine a specific pattern of reversal event occurrences. X indicates the growth rate in the first four months of the current month, and the target variable Y indicates the type of event (UpWard, DownWard) in a future month. The C4.5 algorithm was chosen to create a decision tree using the data set (X, Y) in Tables 13–15. The generated decision tree is shown in Figures 8–10, and this study can test the branching rules through the decision tree and obtain the prediction accuracy of three indexes, as shown in Table 16. The accuracy at PPI_IPD_10 is the highest, with a prediction accuracy of 50%.

The experimental results show that the decision tree scheme generated by PPI_IPD_10 can predict the events to

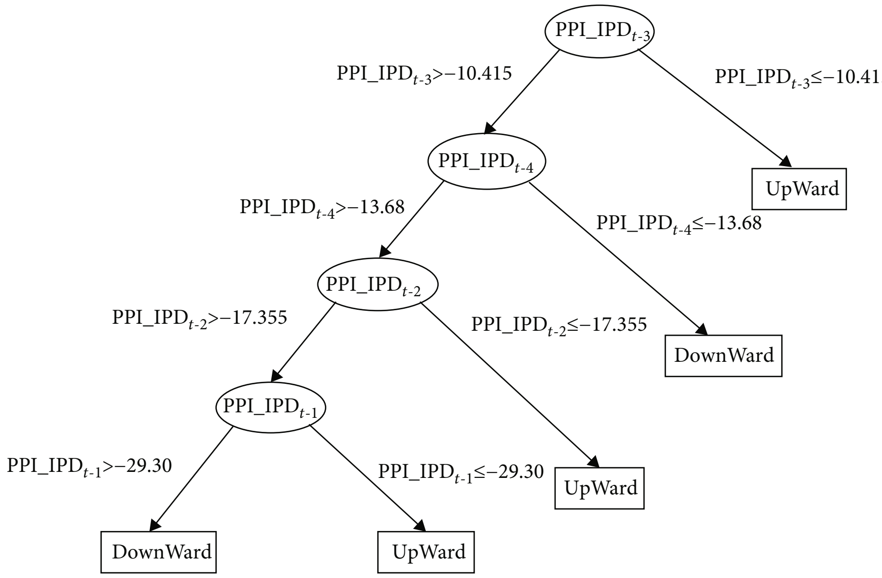

Figure 9: Decision tree formed by PPI_IPD_10 value change.

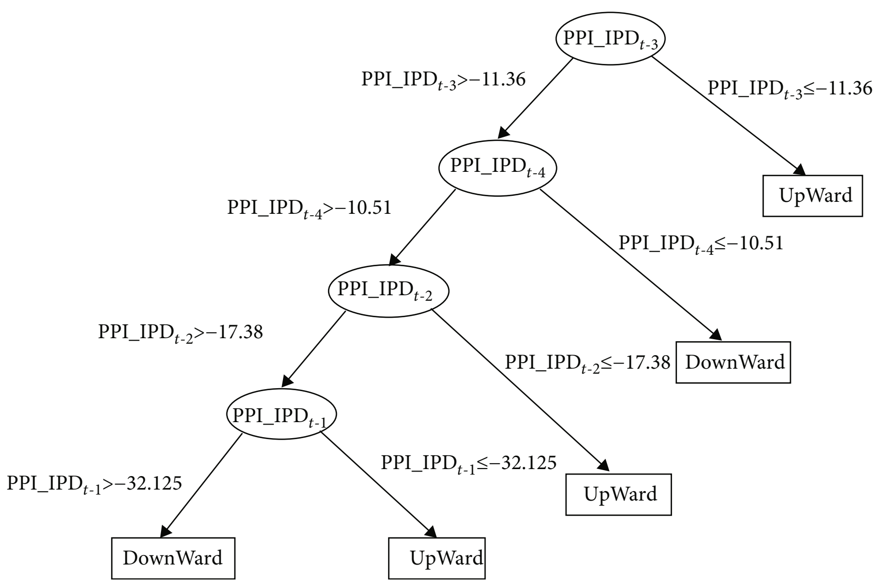

Figure 10: Decision tree formed by PPI_IPD_20 value change.

Table 16: Accuracy of predicted for decision trees generated by three indexes.

Index type	Symbols	Accuracy
Trading volume > 0% composition of the index	PPI_IPD	25%
Trading volume > 10% composition of the index	PPI_IPD_10	50%
Trading volume > 20% composition of the index	PPI_IPD_20	25%

occur in the fifth month through the change of index value in the first four months. The accuracy is higher than in PPI_IPD and PPI_IPD_20. Enterprise analysts have better results when using the price index compiled by the minimum threshold of 10%.

5. Conclusion

The design of Imported Pork Producer Declaration Price Index (PPI_IPD) fills the lacunae in imported meat price index. It provides a new tool to understand China's imported pork market and can be helpful in understanding global food tendency.

Currently, to the best of our knowledge, there is no index to measure the volatility of imported pork prices in China. Basic processing, filtering, weighting, and dynamic adjustments are performed through first-hand imported pork customs declaration price data. Therefore, the designed index is scientifically and practically feasible. This study analyzed the dynamic correlation between the PPI_IPD index and the market prices of pork and the stock trend of pork-related industries in China, through an empirical study. The correlation coefficient is maintained between 0.4 and 0.7, indicating that the index is market representative and has a lagging effect. To enrich and improve the imported pork price index system and provide scope for a new underlying index for growing indexing investments, this study considered the current situation in China and set a minimum threshold of 10% on transaction volume, establishing an imported pork price system for China. Experiments have proven that decision trees are successful in searching for hidden rules in large amounts of PPI_IPD data. The visibility of the relationships between node branches and leaves in the tree makes it a suitable method to study investment trading decisions in the imported pork market.

The price index constructed in this study can reflect the actual price trend of imported pork. The PPI_IPD is a vital addition to China's meat price information, which can be helpful to numerous governments, meat processing businesses, and researchers worldwide. In addition, a reasonable price index can reflect the actual market supply and demand, price trend, and market prosperity. The above experiments proved that PPI_IPD has a higher correlation in the stock trend of the current mainstream pork processing companies and demonstrates higher accuracy in terms of designing decision trees using historical growth rates. Therefore, 10% of our trading volume is set as the minimum entry threshold and can be implemented as a trading strategy. It can help governments and companies to make reasonable decisions and investments.

The PPI_IPD proposal offers a useful tool for tracking changes in the price of imported pork from China. The research's limitation is that, as of right now, only decision trees can be used to give business owners and financial professionals a straightforward decision scene, like the ups and downs of a trend. In the future, we will also introduce an expert system based on the proposed PPI_IPD to provide complex and complete trading strategies or trading rules. In future research, deep learning, data mining, and other technologies can be used to continue to explore the economic value behind PPI_IPD.

Data Availability

The data used in the experiments were stock price from Shenzhen Stock Exchange (http://quote.eastmoney.com/center/hszs.html).

Conflicts of Interest

The authors declare no conflicts of interest.

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