Explore Chinese Energy Commodity Prices in Financial Markets using Machine Learning

Yu Cui[1], Tianhao Ma[2]
HITSZ School of Economics and Management, Harbin University of Technology (Shenzhen), Shenzhen, 518055, China[1]
College of Business and Economics, Australian National University, Acton, 2601, Australia[2]

***Abstract*—This study simultaneously investigates the causality and dynamic links between international energy trade and economic price changes, especially in the Chinese commodity market. To get a causal route, it attempts to identify the linear and nonlinear causality among commodity prices, equities, and the exchange rate in China and the United States (US). Here, we adapt multilayer perceptron networks to obtain a nonlinear autoregressive model for causality discovery. After comparing methods without networks, this study proves that the nonlinear causality discovery method using machine learning performs best on simulated data. Subsequently, we apply that causality to actual data; we combine the causal routes, particularly from the machine learning methodology, to investigate the existence of a causal direct or indirect relationship among Chinese commodity prices, long-term interest rates, stock index, and exchange rates in China and the US. The steady-state accuracy of cmlpgranger is 99%. In most cases, the order of judgment accuracy of causality is cmlpgranger > HSICLasso > ARD > LinSVR. The results show that Energy trade as an element of the global economic system. The Chinese commodity price of energy has an interactive relationship with the Chinese commodity price of agricultural products. The significant transmission is from the commodity price of energy to equities, then to the exchange rate, and, finally, to the commodity price of agricultural products.**

Keywords—Chinese commodity price; exchange rate; stock markets; machine learning; international energy trade; global economic system

I. Introduction

As an essential part of the global industrial chain, the price fluctuation of commodities has a tremendous impact on the real economy, and the inflation level has a significant effect. The supply and demand pattern of commodities has changed dramatically since 2020. The COVID-19 pandemic raised energy costs, political instability and increased demand for energy [1], which led to intense fluctuations in international commodity prices. In the post-pandemic era, the evolution of the world pandemic situation is out of sync with the economic recovery of various countries. Under the pressure of green transformation and global development, major developed economies have implemented large-scale fiscal stimulus and super-wide monetary policies. At the same time, there have been profound changes in the international economic and trade landscape, geopolitical factors, extreme climate, and other factors. Global supply and demand patterns. Commodities are generally in short supply [2]. Under the influence of various complex factors, it is very important to sort out the causal logic among the factors affecting commodity prices and clarify the impact of commodity price changes on the macro economy for effectively adjusting policies and overcoming the global economic recession.

China is currently the world's largest consumer country [3]. The continued demand for energy, essential raw materials, and agricultural products has rapidly increased China's commodity imports. China has become the world's largest importer of commodities such as iron ore, aluminum ore, lead ore, nickel-chromium ore, and crude oil [4]. The existing literature in 2018 includes discussions on factors that affect commodity prices. However, the current global indicators mainly consider the role of developed countries, but do not consider China's role and its impact on China.

This study also aims to provide a comprehensive analysis using the machine learning (ML) approach. Although numerous studies have analyzed the factors and effects of international commodities prices, we make full use of the algorithm advantages of ML to integrate our findings with those of previous studies. The majority of applied analyses on this topic used the vector autoregressive (VAR) Granger's tests. Sahlian et.al. used the Granger test to establish the causality between the market capitalization and financial indicators [5]. In the classic linear VAR method, when evaluating the cause of Granger, the maximum delay must be stated. When the relationship between the past of one series and the future of another series does not belong to the model category. The method based on model in the real world may fail [6-8]. This usually occurs when there is a non-linear relationship between the past and future of a series. The nonlinear relationship between the past and the future can be detected by minimizing assumptions about the predicted relationship [9]. For example: Yin Z et al. used multiple repetitive neural networks to demonstrate the effectiveness of nonlinear random time series models. [10] Neural networks can display complex nonlinear and non-auxiliary interactions between inputs and outputs. Some studies introduced the structural learning framework in multi-layer sensor (MLP) and Recurrent neural network (RNN). This led to Granger's nonlinear causal discovery. However, the use of these methods to analyze causal processes between multiple variables is particularly rare in the field of economics.

The surge in oil and food prices over the past decade has prompted a large amount of research to focus on the common flow of crude oil and agricultural products. Then, some studies begin modeling to investigate correlations and connections or pathways. On the contrary, some studies provide evidence of the neutral relationship structure between crude oil and agricultural products. Based on the research of previous generations, the significance and innovation of this study can be summarized in the following three points.

Firstly, we are the first to adopt the ML method instead of traditional economic models. The determination of causal relationships in existing literature is mainly based on the assumptions of econometric models. However, most of these models explore linear relationships. Based on our research, we are the first to use ML to study the causal discovery and relationship between energy and agricultural futures prices. Using ML in this study, we can break the assumptions of the Traditional economy model and find more nonlinear relationships. In addition, compared to other traditional econometric models that only estimate one or two parameters, the ML time size Helping people study time series in time zones and frequency domains

Secondly, we have important evidence in studying the relationship between energy prices and agricultural product prices. In past research, there has been no consensus on the research conclusions, price indicators, and research methods for energy and agricultural product prices at different periods. Country/Region. This study focuses on the prices of China's energy and agricultural futures markets, providing many research conclusions for the literature.

Finally, this study discussed whether this relationship exists and attempted to express causal relationships based on important financial indicators. Most research on the impact of commodity prices focuses on two pairs of relationships. However, this study consists of two or more factors of causality diagram, thus obtained a comprehensive causal path. The media focused on Chinese stock market prices and the exchange rate between China and the United States.

The structure of the remaining parts of this article is as follows: In Section I, we introduced early research related to commodity market reasons or correlations. In Section II, we use motivational datasets to evaluate the effectiveness of machine learning causal discovery methods. After determining the cause-finding ability of these methods, we will use it to analyze the actual data and get the results in Section III. Finally, Section IV summarizes the article.

II. METHODOLOGY AND DATA

A. Adapting Neural Networks for Granger Causality

The Nonlinear Autoregressive Model (NAR) allows XT to dynamically evolve based on typical nonlinearity [11]:

$$x_t = g\left(x_{<t1}, \cdots, x_{<tp}\right) + e_t \tag{1}$$

where $x_{<ti} = \left(\cdots, x_{(t-2)i}, x_{(t-1)i}\right)$ represents the past of sequence i; we assume that the additive noise zero mean e_t.

In a forecasting setting, the mutual modeling of nonlinear functions g typically uses neural networks. Neural networks have a long history in predicting NAR using traditional architectures [12] and the latest deep learning techniques [15]. These methods use MLP, where the input

$$x_{<t} = x_{(t-1):(t-K)} \tag{2}$$

Our main approach is to model each output g_i using a separate MLP to easily clarify the impact of input on output. We call it component-wise MLP (cMLP) [17]. Set g_i in the form of MLP with L−1 layers, and let the vector $h_t^l \in R^H$ denote the values of the m-dimensional lth hidden layer at time t. The discovery and research of nonlinear causal relationships have become more widespread, for example, M Roso et.al (2022) not only focused on theory, but also on how to build Python packages to complete testing [18].

Definition 1. Time series J is a non-causal relationship of time series I if all $\left(x_{<t1}, \cdots, x_{<tp}\right)$ and all $x'_{<tj} \neq x_{<tj}$,

$$g_i\left(x_{<t1}, \cdots, x_{<tj}, \cdots, x_{<tp}\right) = g_i\left(x_{<t1}, \cdots, x'_{<tj}, \cdots, x_{<tp}\right) \tag{3}$$

that is, g_i is invariant to $x_{<tj}$.

The parameters of the neural network are given by weights W and biases b as each layer, $W = \left\{W^1, \ldots, W^L\right\}$ and $b = \left\{b^1, \ldots, b^L\right\}$. To compare with the time series VAR model, we divided the weight of the first layer into time delays, $W^1 = \left\{W^{11}, \ldots, W^{1K}\right\}$. The parameter sizes include $W^1 \in R^{H \times pK}$, $W^l \in R^{H \times H}$ for $1 < l < L$, $W^l \in R^H$, $b^l \in R^H$ for $l < L$ and $b^L \in R$. Using this notation, the vector of first layer hidden values at time t is given by

$$h_t^1 = \sigma\left(\sum_{k=1}^{K} W^{1k} x_{t-k} + b^1\right) \tag{4}$$

where σ is an activation function [19].

In Equation (4), if the jth column of the first layer weight matrix, $W_{:j}^{1k}$, contains zeros for all k, then series j does not Granger-cause series i. That is, $x_{(t-k)j}$ for all k does not affect the hidden cell h_t^1. So according to the definition 1 output x_{ti}, we can see that g_i divided by $x_{<tj}$ remains unchanged.

B. Creating Benchmark Datasets

1) Group1: Lorenz-96 model: We use these two methods to detect Granger's causal network from P's simulated Lorenz-96 data. Find the impact of many attributes in different ways [11].

The continuous dynamics of the P Vilorenz model will be obtained from the following styles.

$$\frac{dx_{ti}}{dt} = \left(x_{t(i+1)} - x_{t(i-2)}\right) x_{t(i-1)} - x_{ti} + F \tag{5}$$

where $x_{t(-1)} = x_{t(p-1)}$, $x_{t0} = x_{tp}$, $x_{t(p+1)} = x_{t1}$ and F is a mandatory constant that determines the degree of nonlinearity and chaos in the set.

2) Group2: Nonstationary data: Due to the fact that most of the attributes we want to check are not smooth in practice, we will add trends to the Lorenz-96 P dimension data to obtain the data. The second set of extended Dickey Fuller (ADFuller) checks can be used to test the unit root directory within a single variable process in the presence of sequence relationships. We use ADFuller to test whether the data is stable.

$$\mathrm{Trend}_t = \mathrm{Trend}_{t-1} + \left(\mathrm{Trend}_I - \mathrm{Trend}_0\right)/I \tag{6}$$

Here, t∈ (0, I), I is the length of features and Trend is linear.

As shown in Table I, we take P as 5 and obtain the results of two datasets with P values:

TABLE I. ADFULLER TEST OF DATA (CALCULATED BY AUTHORS)

Group1	Adfuller P_Value		Group2	Adfuller P_Value	
X_1	6.641034e-22	stationary	X_1 +Trend	0.689549	Nonstationary
X_2	5.266443e-18	stationary	X_2 +Trend	0.716672	Nonstationary
X_3	5.218544e-10	stationary	X_3 +Trend	0.700451	Nonstationary
X_4	3.249791e-14	stationary	X_4 +Trend	0.706434	Nonstationary
X_5	8.472980e-12	stationary	X_5 +Trend	0.797429	Nonstationary

C. Comparing Models for Granger Causality

We compare four methods on different numbers of features using stationary and nonstationary data. The four methods are LinSVR2, automatic relevance determination (ARD), HSIC-Lasso, and CMLP-Granger.

The basic support vector regression (SVR) concepts are introduced by Schölkopf and Smola; Linear SVR (LinSVR) is a special case of SVR with a linear axis. Huang and Cai improved SVR and used these methods to select features. The advantage of LinSVR is that due to the small complexity of the model, the results are easy to interpret. However, it cannot recognize nonlinear relationships that typically occur in real data.

ARD was proposed by MacKay based on the Bayes model, which effectively selects relevant features through preliminary training. Evaluate initial hyperparameters by maximizing the probability in the data. This process is called evidence augmentation, or maximizing the second type of likelihood. Wipf and Nagarajan [20] applied the ARD method to prune large numbers of irrelevant features, leading to a sparse explanatory subset and demonstrating that the ARD prior maintains advantages compared to conventional priors in feature selection.

TABLE II. RESULTS OF DIFFERENT METHODS (CALCULATED BY AUTHORS.)

Methods	x_num	Stationary	Nonstationary
		Accuracy	*Accuracy*
ARD	**5**	**100%**	60%
HSICLasso	**5**	**100%**	60%
LinSVR	5	76%	60%
cmlpgranger	5	80%	72%
ARD	15	56%	76%
HSICLasso	15	92%	67%
LinSVR	15	80%	80%
cmlpgranger	**15**	**100%**	**97%**
ARD	35	63%	64%
HSICLasso	35	96%	85%
LinSVR	35	63%	63%
cmlpgranger	**35**	**99%**	**98%**
ARD	50	59%	59%
HSICLasso	50	98%	90%
LinSVR	50	58%	58%
cmlpgranger	**50**	**99%**	**97%**
ARD	100	56%	55%
HSICLasso	100	98%	85%
LinSVR	100	54%	54%
cmlpgranger	**100**	**98%**	**97%**

Freidling et al. [21] improved the least absolute shrinkage and selection operator (Lasso) method on feature selection by integrating Lasso and particular kernel functions with kernel-based independence measures such as the Hilbert–Schmidt independence criterion (HSIC). Compared to the former Lasso methods, the HSICLasso can capture nonlinear dependency with a clear statistical interpretation and deal with high-dimensional feature selection scenarios in which the number of training samples is smaller than that of features.

In 2021, Alex Tank, Ian Covert et al. [22] use time series normal neural network Model selection framework of Granger nonlinear causality. These researchers applied the multi-layer sensor module (cMLP) and the long run and short run memory architecture of the module. (cLSTM) includes related sparsity, which promotes penalties for network inbound weight, thus selecting Granger demonstrated the construction of Granger causality diagram, which is the correct basis for linear and nonlinear settings.

In Table II, the results can be summarized into three points. (1) In most cases, the order of judgment accuracy of causality is cmlpgranger > HSICLasso > ARD > LinSVR. (2) The performance of cmlpgranger varies with the number of factors. When the number of distinguishing factors is greater than 5, it is far better than other methods. (3) cmlpgranger also performs well for nonstationary data. When the data are nonstationary, the accuracy of the method in judging causality is significantly higher than that of other models.

III. RESULTS

Through simulated data, proved cmlpgranger in nonlinear nonstationary has good capability of causal relationships found in the data. Therefore, we determine the cause and effect of the actual data of the Chinese futures market by integrating the results of several causality methods. Specifically, we want to ascertain how the relationship between the commodity prices of energy affects that of agricultural products and its specific impact path.

In order to assess the causal relationship of commodity prices, we have adopted from the Ministry of Commerce of China's commodity price index (CCPI) international commodity prices. Financial indicators covering the stock market, bond market, futures market, interest rate, credit market, and foreign exchange market are extracted from the Wind Economic Database as financial market factors affecting commodities prices. All data begin from June 2006 to October 2021 monthly. The nomenclature of indicators is shown in Table III.

Finally, for each method, we obtain a causality matrix, where $a_{i,j}$ in the matrix equal to 1 indicates that the *j*th factor is the cause of the *i*th factor. Otherwise, there is no apparent causality between the two elements. To acquire accurate results, we synthesize the conclusions of the models that perform well on the simulation dataset. Table IV shows the causality result confirmed by cmlpgranger. Table V shows the causality result proved through the HSICLasso and ARD methods.

TABLE III. NOMENCLATURE (CALCULATED BY AUTHORS.)

Full Name	Abbreviation	Full Name	Abbreviation
China commodity price index_ Total index	CCPI_T	S&P 500 index	SP500
China commodity price index_ Energy	CCPI_E	CSI 500 Index	CSI500
China commodity price index_ Non-ferrous metals	CCPI_M	US discount rate	US_DR
China commodity price index_Agricultural products	CCPI_A	CN discount rate	CN_DR
The US dollar/RMB exchange rate	USDCNY	US10-year Treasury yield	US_TB10Y
The Dollar index	DI	CN10-year Treasury yield	CN_TB10Y

TABLE IV. CAUSALITY RESULTS OF THE CMLPGRANGER METHOD (CALCULATED BY AUTHORS.)

Cmlpgranger	CCPI_E	CCPI_M	CCPI_A	US_TB10Y	USDCNY	DI	CSI500	SP500	CN_TB10Y
CCPI_E	1	1	0	0	1	0	0	0	0
CCPI_M	0	1	0	0	0	0	0	1	0
CCPI_A	0	0	0	0	0	0	0	1	0
US_TB10Y	0	1	0	0	0	0	0	0	0
USDCNY	0	0	0	0	0	0	0	0	0
DI	0	0	0	0	1	1	0	0	0
CSI500	1	0	0	0	1	0	1	1	0
SP500	0	1	0	0	0	0	0	1	0
CN_TB10Y	0	1	0	0	0	0	0	0	1

TABLE V. INTERSECTION OF CAUSALITY RESULTS OF THE HSICLASSO AND ARD METHODS (CALCULATED BY AUTHORS.)

HSICLasso&ARD	CCPI_E	CCPI_M	CCPI_A	US_TB10Y	USDCNY	DI	CSI500	SP500	CN_TB10Y
CCPI_E	1	1	0	0	0	1	0	0	0
CCPI_M	0	1	1	0	1	1	0	0	0
CCPI_A	0	0	1	0	1	1	0	0	0
US_TB10Y	0	1	1	1	0	0	0	0	0
USDCNY	0	0	1	0	1	1	0	0	1
DI	0	0	0	0	0	1	1	0	1
CSI500	1	0	0	0	0	0	1	0	0
SP500	0	0	0	0	0	0	0	0	0
CN_TB10Y	0	0	0	0	0	0	0	0	0

Combining the results of the two methods, we can use Fig. 1 to show the relationship between futures market prices and other economic indicators. The bold black line shows the causal relationship, which is proved by three methods (cmlpgranger, HSICLasso, and ARD). The black line indicates the causal relationship, which is proved by two methods (HSICLasso and ARD). The red dotted line shows the causal relationship proved by cmlpgranger method, which can be indirectly verified by the other two methods. The arrow points from cause to result.

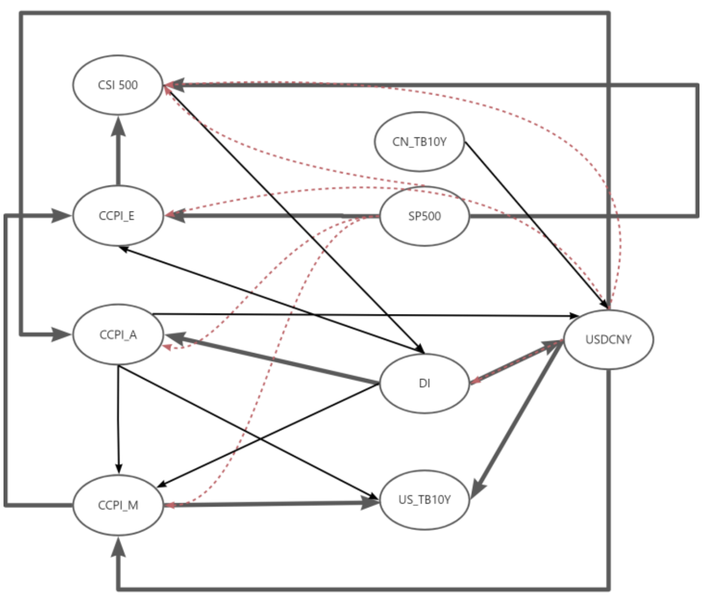

Fig. 1. Causality routes (Calculated by authors.).

Thus, we can conclude that the CCPI_E and CCPI_A have an interactive relationship. The Chinese commodity price of energy will affect the CSI500, thereby affecting the dollar index. The similar conclusion given by Shabir et. al. show that the impact of oil prices and exchange rate on stock prices exists and varies across bullish, bearish, and normal states of the stock market [23]. [23] The dollar index will also affect the exchange rate between China and the US and eventually transmit to the China commodity price of agricultural products. Conversely, the China commodity price of agricultural products will affect the China commodity price of non-ferrous metals and finally transmit to energy prices.

Other researchers have also investigated the conclusion that CCPI_E affects the direction of CCPI_A, and analyzed the relationship between oil prices. Food (agricultural product prices) and exchange rates, as oil prices are transmitted to the local agricultural market through exchange rates. Nazlioglu and Soytas conducted a study on global oil and agricultural prices, explaining the relative strength of the US dollar [24]. Awartani et al. pointed out that the oil market is the main source and risk transfer for stocks, euro/dollar exchange rates, precious metals, and agricultural products [25]. In our results, we observe the evidence favoring this argument with respect to Chinese commodity prices.

IV. CONCLUSIONS

In this study, we use monthly data from the Chinese financial market from June 2006 to October 2021 to investigate the causal route between the commodity prices of energy and agricultural products. Unlike traditional econometric models, we apply the ML method for the first time to examine this issue. Using these methods, we find that the energy commodity price is vital. It can affect equities changes represented by the CSI 500 Index, thus affecting the exchange rate between China and the US and eventually causing changes in the prices of agricultural products. In comparison with previous studies, we find a correlation between the energy commodity price and agricultural products but emphasize indirect media in causality.

The conclusions drawn in this study led to further considerations. First, we should remain alert to changes in energy commodity prices. Since the commodity price of energy is likely to affect the Chinese capital market price. Second, the exchange rate influences the commodity prices of different varieties in China, indicating China is still highly dependent on foreign countries in terms of the import of products involved in the commodity market. In 2022, under the general environment of long-term inflation in the US, the exchange rate between China and the United States breaking 7, the stalemate in the Russia–Ukraine war, and the continued slowdown in global economic growth, the price of China's futures market will also be volatile under the influence of the strong US dollar. Third, based on the results, most causal paths reflect that the prices of various commodities in China or the prices of China's capital markets are always affected. Still, there is no obvious path to show the impact of China's factors on American financial indicators. This suggests that there is still a long way to go to improve the Chinese commodity market.

But there is still much work to be done. First, causality may change over time. While we consider the beginning year of COVID-19, the actual time when significant economic changes will occur is 2-3 years after COVID-19, not 2021. As new data becomes available, we should pay attention to these changes. Second, more research is needed to prove the effectiveness of machine learning methods in doing causal discovery.

Supplementary Materials: The following supporting information can be downloaded at: www.mdpi.com/xxx/s1, Fig. 1. Causality routes; Table I: ADFuller test of data; Table II: Results of different methods; Table III: Nomenclature; Table IV: Causality results of the cmlpgranger method; Table V: Intersection of causality results of the HSICLasso and ARD methods.

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