# INFORMATIONAL DISCONTINUITY IN SOYBEAN FUTURES PRICE FROM THE 2018-2019 SINO-AMERICA TRADE WAR

A Thesis

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## ABSTRACT

There are plenty of studies testing and verifying the price signaling effects between China and US futures markets. This paper is built up based on this consensus but further elaborate on method application. Results show that previous patterns of price signaling effect on soybean futures prices between China and US no longer exist after the US-China trade war in 2018, during which the trade of soybeans was adversely affected and almost stopped. Different from previous studies, this paper differentiates price signaling effects between opening prices and closing prices of soybean futures, building up a circulating price signaling structure. We also consider signaling effect between US soybean futures price and Chinses spot price. Besides, existing studies typically predict future price shocks by simulations. This paper applies an existing shock, the 2018 US-China trade war, to examine whether the price signaling effects still exist.


Key words: US-China trade war, price signaling, soybean futures

This thesis is dedicated to my parents and my future cat.

# ACKNOWLEDGMENTS

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# CHAPTER 1 INTRODUCTION

## 1.1 Literature review

Since 2012, China has become the predominant market for US soybean exports (Hansen, J., Marchant, M. A., Tuan, F., & Somwaru, A., 2017). There is plenty of research that sheds light on price signaling effects between US and Chinese markets, both futures and spot. Fung, H. G., Wilson Liu, Q., and Tse, Y. (2010) argue that there is a significant relationship between US and Shanghai futures markets for copper and aluminum. Hua, R., and Chen, B. showed similar results and conducted research on more products including soybeans and wheat (Hua, R., & Chen, B., 2007). Hung-Gay Fung, Wai K. Leung and Xiaoqing Eleanor Xu proved that soybeans, with less Chinese governmental control, is subject to influence from the US soybean futures market. The US futures market plays a dominant role in transmitting trading information to the Chinese market (Fung, H. G., Leung, W. K., & Xu, X. E., 2003). It is widely agreed that US agricultural futures markets have a dominant pricing role, but this dominant role is fading away and China is developing its own pricing system (Liu, B. J., Wang, Y., Wang, J., Wu, X., & Zhang, S., 2015). Also, Chinese markets have been gaining power in price discovery (Ke, Y., Li, C., McKenzie, A., & Liu, P. 2019). There is significant bi-directional dependence between Chinese and US markets across commodities, including soybeans, wheat, corn and sugar. China's dependence on US markets is greater than US dependence on China's markets (Jiang, H., Su, J. J., Todorova, N., & Roca, E., 2016). In the soybean futures market itself, the US market has taken the leading role. The overnight return of U.S. soybean futures and the daytime return of Chinese No. 1 soybean futures simultaneously affect each other (Li, C., & Hayes, D. J., 2017). The bi-directional spillover effect is also detected between soybean futures markets of the two countries (Zhang, B., 2015). However, some researchers also argue that the signaling effects between China and US soybean futures are equally influential in both directions (Han, L., Liang, R., & Tang, K. E., 2013).

A trade war between China and US could adversely affect the original pattern of stability between these two nations, as well as have effects on price signaling. Although the US's initial objectives for starting a trade war were to cut trade deficits and protect high-tech industries (Liu, T., & Woo, W. T., 2018), other industries could be impacted as well when China gets its revenge. Not surprisingly, China announced its additional 25% import tariff on US soybeans, which would result in painful hardship for US soybean farmers and a sharp decline in the Chinese soybean supply (Zheng, Y., Wood, D., Wang, H. H., & Jones, J. P., 2018). In the long run, neither of the two countries would benefit from this war; it is other soybean suppliers like Brazil and Argentina that would reap the profits (Zhou, Y., Baylis, K., Coppess, J., & Xie, Q., 2018).

## 1.2 Introduction to theories

In this paper, we develop our reflections and conclusions based on the results of previous studies and on the classical theories of international trade and standard framework about futures. We summarize these theories in this section.

### 1.2.1 Comparative advantage

The comparative advantage model (Krugman, 2008) is a classical model illustrating how countries would specialize in producing certain products. The basic idea is represented as follows:

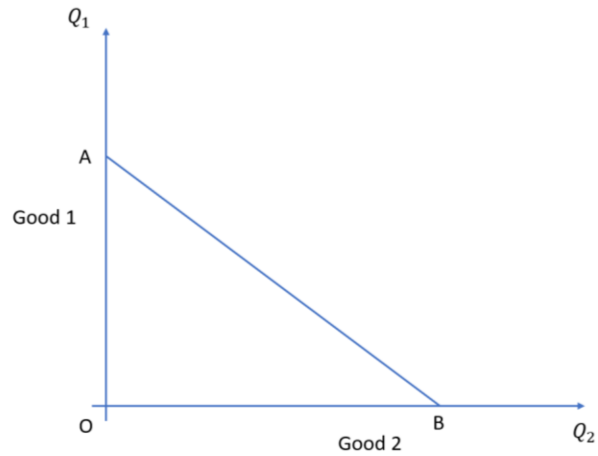


Figure 1: comparative advantage

We will elaborate this theory with the help of the simplest example. In this example, we set two assumptions. First, we assume that a country, as a closed economy, has a given labor supply and technology that can be allocated to produce either good 1 or good 2 or both. Due to different characteristics of the products, the requirements of labor and technology for producing each good varies. As shown above, if all resources are used to produce good 1, the country can supply at most A units of good 1. Similarly, if all labor and technology is concentrated in producing good 2, there will be B units of good 2 available. As the relationship between producing good 1 and 2 is linear, it is easy to conclude that any combination in the line AB is also feasible and deploys same amount of total resources as that in A and B. The line AB, therefore, is called a production possibility curve. Note that when the country is producing on line AB, there is no extra resource left; thus there is a built-in assumption of a zero-unemployment rate. Apparently, any point inside area OAB is also feasible, except that they are not exhausting all resources and do not create unemployment. Second, we assume that the market is one of perfect competition, which means the price of the commodity produced is equal to the cost of producing it.

Based on this assumption, we can come up with the following relationship between price and resource cost:

$$\mathrm{P} = \frac{\mathrm{R}}{\mathrm{Q}}$$

Where P refers to the unit price of that product, R is total resources used and Q is the quantity produced given R. Based on this equation, we can derive the price ratio of good 1 and good 2:

$$\frac{P_1}{P_2} = \frac{R_1/Q_1}{R_2/Q_2}$$

Which, stated differently, also represents the marginal rate of substitution between good 1 and good 2. The marginal rate of substitution measures how much revenue from good 1 will be sacrificed in order to produce one more unit of good 2, and vice versa.

Now let's expand this simple example and add international trade to the model.

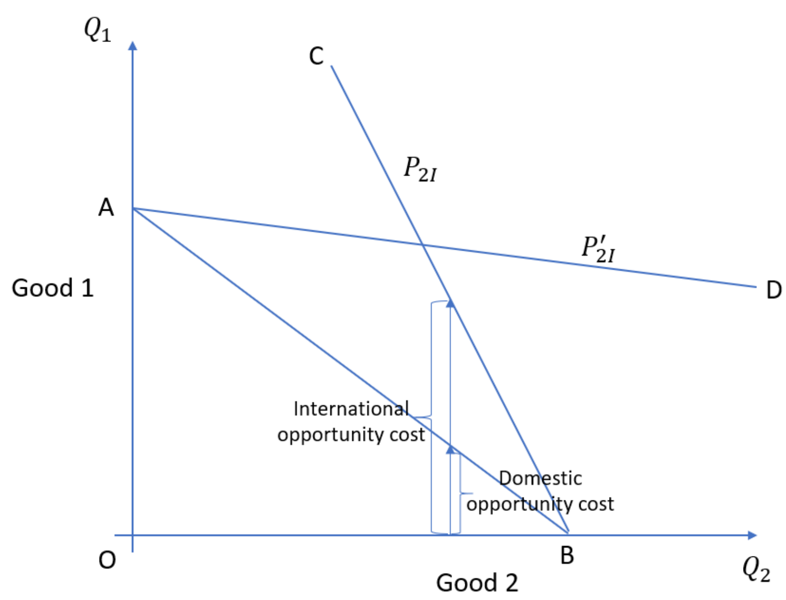


Figure 2: opportunity cost

According to the price ratio, we can calculate the slope of the curve above:

$$\frac{Q_1}{Q_2} = \frac{L_1/P_1}{L_2/P_2}$$

Keeping constant the price of good 1, if the price for good 2 is higher in the international market, as shown in line BC, the revenue loss, or opportunity cost for producing one unit less of good 2, is higher than that in the domestic market. Which also means that if the country allocates all its resources to produce good 2 and trade them in international market, they can exchange more units of good 1 than if it produced good 1 by itself. The country is said to have a comparative advantage in producing good 2. Seemingly, the country will use all its resources in good 2 production which ends at point B. On the contrary, if the international price for good 2 is less than the price in the domestic market, then the country will specialize in producing good 1. Comparative advantage now resides in good 1.

### 1.2.2 Tariffs on international trade

Tariffs have long been regarded as a barrier to international trade but also an means to protect domestically produced goods. The effect of tariffs is basically to increase the price of imported goods, forcing these goods to be sold at a higher price domestically. In the graph below, we show the basic mechanism of a tariff.

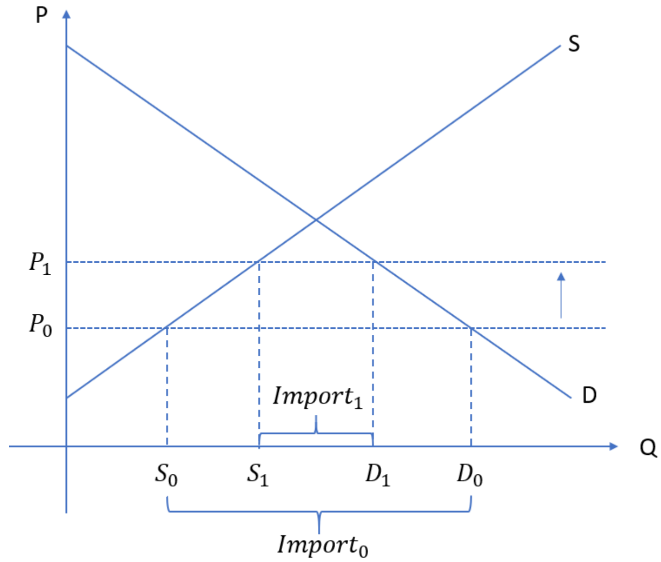


Figure 3: effect of tariff on import

Suppose, in a given country with supply and demand as shown above, the market price may not always be the one that clears the market. Hence, it will need to import goods from the international market to cover the gap between demand and supply. The quantity it imports depends on the international price of the good. When international price is $P_0$, domestic supply lies at $S_0$ but demand is higher at $D_0$. In order to meet domestic demand, the shortfall amount will be satisfied by import; this amount is denoted as $Import_0$. Now let's assume an additional tariff is imposed on the good and the price increases to $P_1$. Domestic supply increases to $S_1$ due to the higher price and profitability, while domestic demand decreases to $D_1$. The gap between supply and demand becomes smaller, so the country will import less, denoted as $Import_1$, from the international market. A rising price is definitely bad news for domestic consumers; the consumer surplus will be consumed unless an alternative supply is found or there is an attempt to avoid tariffs. This is how tariffs adversely affect consumer purchases.

### 1.2.3 Three panel trade

Studying tariff on a broad level gives three panel trade diagram shows below (McCalla, A. F., & Josling, T. E. 1985).

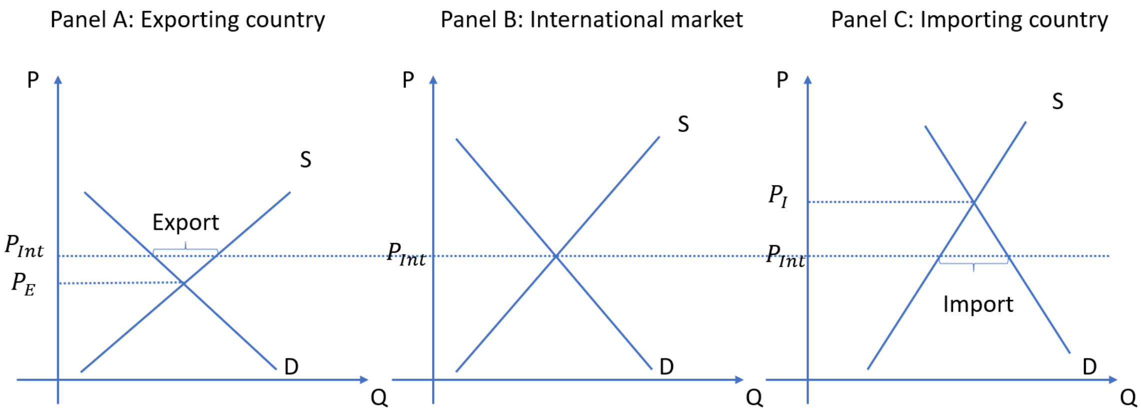


Figure 4: basic three panel trade

Suppose there is no tariff imposed. For a commodity traded in international market, there will be an equilibrium international price decided by total international supply and demand, denoted as $P_{Int}$. All countries will either export or import goods at this price. For an exporting country, domestic price is lower than international price, leaving extra supply to be exported. For an importing country, domestic price is higher and results in insufficient supply, which will be compensated by import.

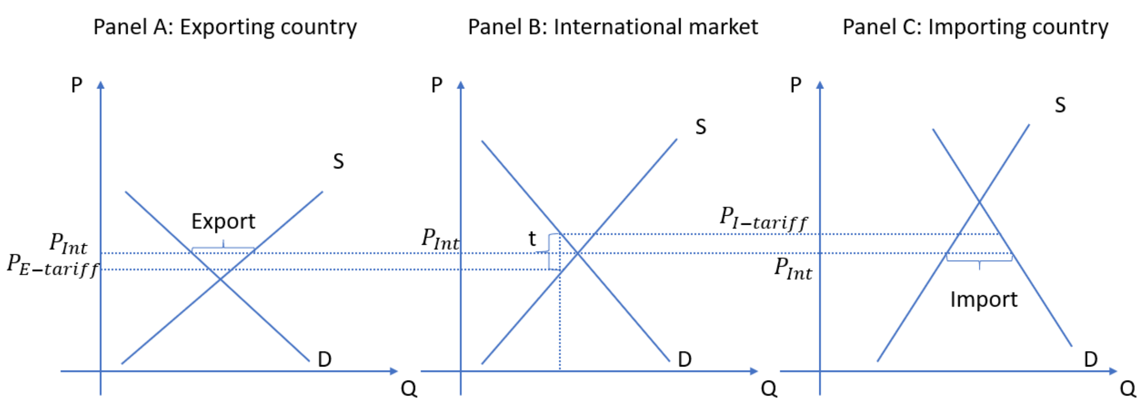

Figure 5: tariff effect on three panel trade

Now assume the import country imposes a tariff on an imported good, which makes it more expensive than the international equilibrium price and reduces import level. Due to the lower import amount, the exporting country needs to cut the export price in order to maintain business and results in less goods exported. The difference between the new import price and the new export price is the tariff amount, assuming no other restriction exists. Note that both countries are small countries and have little effect on world markets, so there is no change in the international market's price equilibrium.

However, if the two nations are powerful and have a significant effect on the international market, there could be a new equilibrium price in the international market. In the following, we show a possible pattern after the imposition of a tariff.

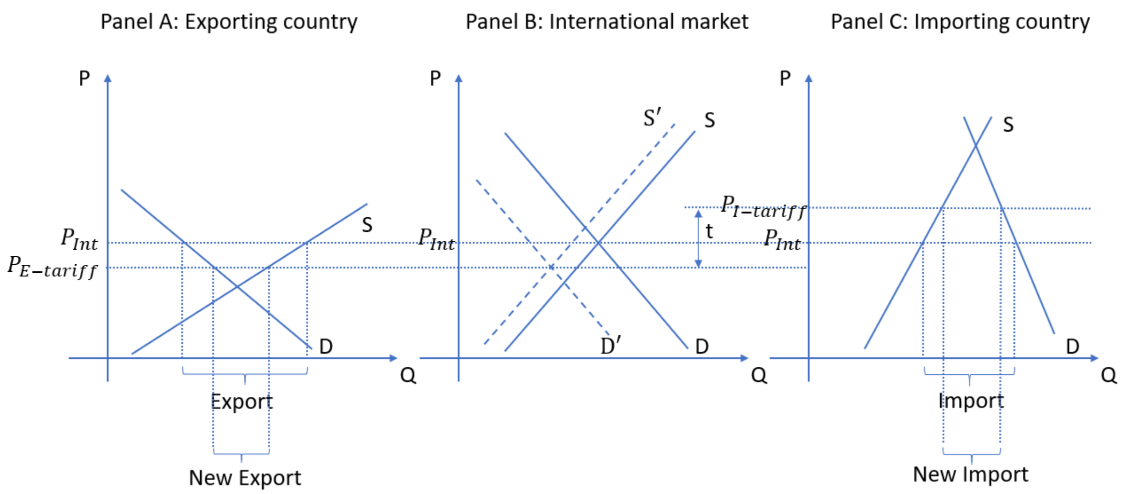


Figure 6: three panel trade for large countries

Just as before, when the importing country announces a tariff, the price for imported goods increases and the import level decreases. Because the importing country is powerful in the international market, the total demand in the international market decreases. To deal with tariff issue and rebuild equilibrium, the exporting country would need to cut the export price and reduce export level. The supply curve for the international market will shift leftwards accordingly. The new equilibrium price will be lower than before, while trade volume also decreases.

However, for China and US, the situation could be more sophisticated than is suggested by the models, in that there is political interference in the system rather than just the imposition of a tariff. But we can still analyze a possible result.

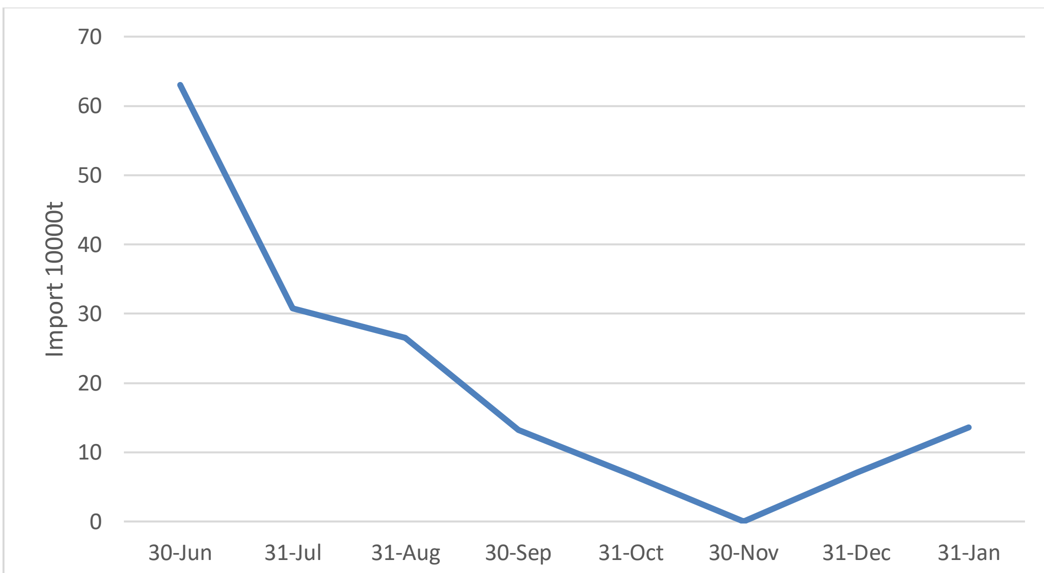


Figure 7: China import amount after war

From the above graph we can see that after the declaration of trade war in June 2018, the import amount from US to China declined rapidly to zero within 5 months. Then after November, the volume started to pick up slightly. We will try to analyze the change on trade panel based on this import pattern.

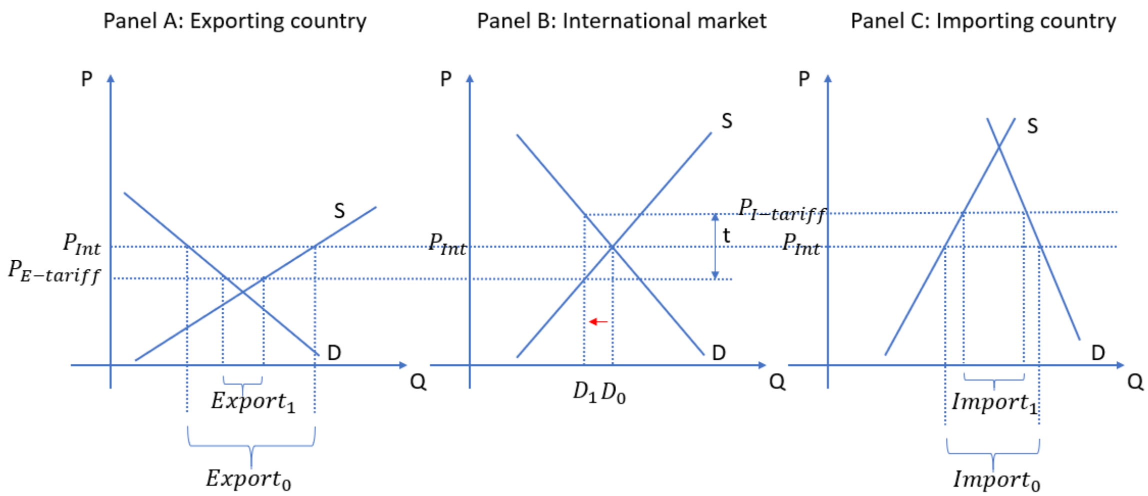


Figure 8: China-US three panel trade

Differing from the standard panel trade model for a tariff, the tariff imposed by the Chinese government was not just for the purpose of monitoring the market, but rather for retaliation. Therefore, the effects caused by the tariff could be more complicated. Let's separate the effect of the tariff into two parts; one is pure economic effect, the other is emotional effect.

Economically speaking, as 25% tariff was imposed on US imported soybeans, there could be multiple effects on both demand curve and prices. We first look at the effects on prices, and for the simplicity, we assume the demand curve kept unchanged when tariff was imposed. Due to higher tariff, domestic soybean price in China would rise from $P_{Int}$ to $P_{I-tariff}$, resulting in less import. The less import demand and higher price were reflected in the international market and the initial equilibrium was broken. Consequently, international demand decreased along the demand curve from $D_0$ to $D_1$. The decreased demand also put downside pressure on US soybean price, causing US price decreased from $P_{Int}$ to $P_{E-tariff}$.

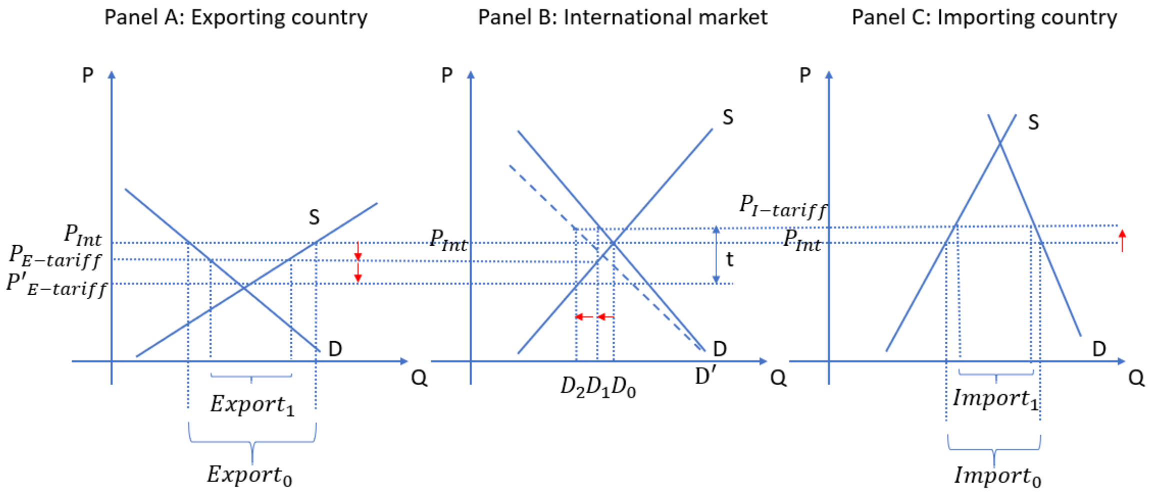


Figure 9: tariff effect on price

Now let's take the demand curve shift into consideration. First, the increased tariff made domestic soybean price higher than before. This higher price would force the demand to shrink, so demand curve in international market would shift leftward. Second, the retaliate tariff was in ad valorem type which levied itself. Even the international price remained unchanged, which was impossible but just for simplicity, the domestic demand would decrease due to higher tariff. So higher tariff made the demand curve more elastic. International demand would further decrease. This would result in both lower export price and export volume in US. Those effects are aligned with what we have been discussing with regard to the standard model for a tariff. Consequently, the total trade volume decreased, together with a higher import price in China and a lower export price in US. All these effects were clearly observed in the data.

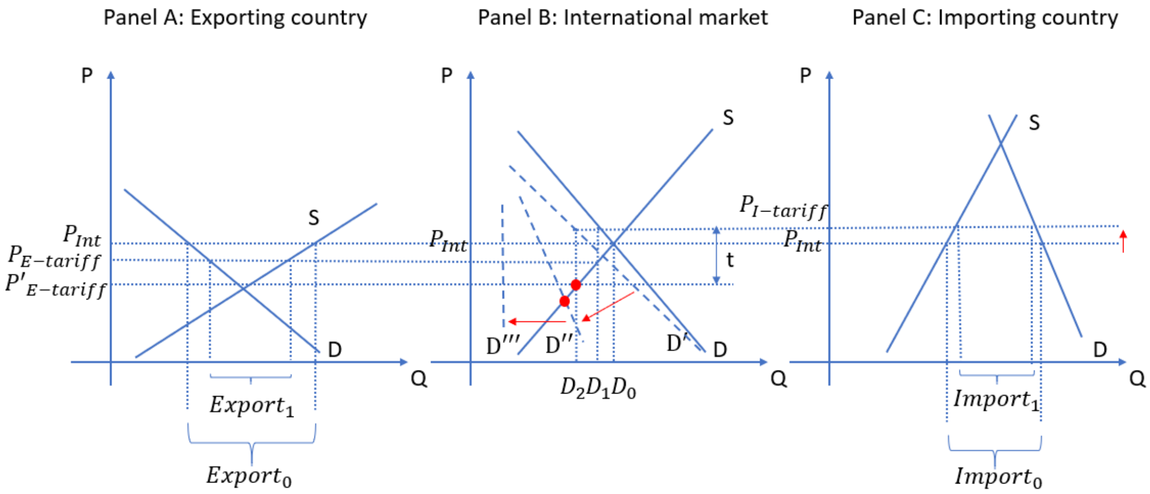


Figure 10: emotional effect on trade

In addition to the economic effect, there might also be an emotional effect caused by the retaliatory tariff. The Chinese people, after the trade war began, suffered from incredibly high tariff and might be unwilling to import soybeans from US, which could possibly make the demand curve more inelastic than before. The international equilibrium price would further decrease, and trade volume also would decline. The international market between China and US would shrink dramatically. As negative emotion increased, the demand curve could become totally inelastic, which would mean that China simply refused any import from the US. When that happened, the international soybean market between China and US would no longer exist. Soybeans that should have been exported to China would be dumped into the US domestic market, thereby increasing supply and decreasing US spot price. Besides, China would have to find an alternative supplier such as Argentina to bridge the demand gap, and the new import price would be subject to negotiations with other countries. Finally, connections between China and US then disappear. This explains not only 0 import in November, but also the deviated movement of the Chinese spot price and the US spot price.

Based on the analysis above, it is reasonable to conclude that two markets could be segmented due to retaliate tariff. US domestic soybean price can no longer effectively influence international market or Chinese market. If there was any price signaling effect in the past, it could be difficult to detect in the future.

### 1.2.4 Pricing of futures contracts

In this paper, we analyze the price relationship with futures prices included. There is much research regarding futures pricing, and we use the authoritative research by John C Hull (Hull, J. C. 2003). A futures contract is a standard contract traded in exchange, stating a future obligation to delivering or buy a certain amount of underlying assets, at a pre-specified price. Futures contract typically has comprehensive specifications including delivery price, contract size, underlying asset and grade, maturity, delivery method and location, etc. The standardized specifications make futures market very liquid and futures are widely used in hedging or speculating against underlying assets.

The price of futures is determined using No Arbitrage Principles, and the formula can be written thus:

$$\mathrm{F} = Se^{(r+u-y)T}$$

Where F refers to futures price determined at the initiation of contract, S is the spot market price of underlying asset when the two parties enter into the contract. T is the maturity of the futures, r is risk-free rate, u is storage cost, y represents convenience yield.

Based on this formula, we can calculate the implied price of futures contract. Note that futures price is not equal to the spot price. The difference between futures price and spot price is called basis, defined as:

$$\text{basis} = \text{spot price} - \text{futures price}$$

Basis can be either positive or negative, depending on the specific market conditions. Traditionally, there are two kinds of markets, contango or backwardation. Contango market refers to market where futures price is higher than spot price, backwardation market represents higher spot price, denoted as follows:

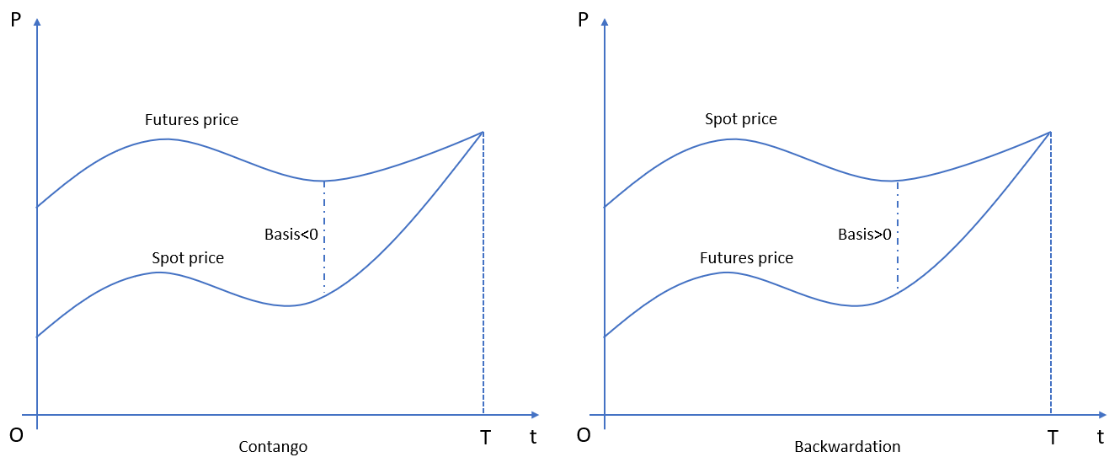


Figure 11: basis and its convergence

Assuming there is no storage cost or convenience yield, the pricing formula will be simplified, and the futures price converges with the spot price at the maturity. This is because the futures price at its maturity date is simply the futures price with a maturity of 0; in another words, the spot price. If this is not satisfied, there might be arbitrage opportunities. For commodity futures, however, failure to converge does not necessarily mean arbitrage opportunities. As underlying assets for commodity futures are physically existent, there is a transportation cost for the delivery commodity to be shipped from storage to designated delivery locations. The difference between the spot price and the futures price, in this situation, refers mainly to transportation cost.

We know that under certain conditions, futures price would converge with spot price at the maturity. Will this also mean that we could predict future spot price by looking at futures price? Before the maturity date approached, is the futures price equals to expected spot price? There is no consensus regarding these issues, but some theories stand out and give reasonable explanations.

Keynes and Hicks: According to these two economists, there are two kinds of participants in futures market, speculators and hedgers. If speculators take more long positions and hedgers take more short positions, then the futures price will be higher than expected spot price. To clarify this, we first look at those two kinds of investors. Hedgers are defined as those who hold and prepare to trade underlying commodities in some future date. The top priority of hedgers is to control their future trading price, or to maintain certainty. In order to guarantee price certainty and eliminate risk, they are willing to sacrifice the possible gains in the future. Speculators, on the other hand, refer to those who do not have underlying asset in hands and only entering the market and betting on price movements. The main purpose for speculators is to pocket capital gains from price movements, so they only trade when the price favors their positions. Since derivatives market is a zero-sum market, the gains of one side must be loss for another side. When speculators hold more long positions and hedgers hold more short positions, it is highly possible that gains are for speculators and loss are for hedgers. Then the futures price will be inflated and higher than expected future spot price.

Risk and return: This theory involves in constructing a portfolio with futures contract and risk-free assets. Specifically, speculators enter into a long position of t-maturity futures contract at price P, then invest present value of P to risk free investment.

At the maturity, speculators will use the risk-free investment proceeds to buy underlying assets. By making the portfolio hedged, there is no non-systematic risk. The only risk for the portfolio is systematic risk, which requires a compensation of risk-free return. After some mathematical derivations, it can be proved that the futures price is equal to expected spot price.

Clearly, the two theories above are valid only when certain market conditions are satisfied. So, there is no consensus on which one really reflects the truth. It is difficult to verify the true market conditions in US and China, but what can be inferred from two theories is that the futures price is somehow linked to the spot price. As the maturity date approaches, spot price and futures price should get closer, although not necessarily become same in the end.

CHAPTER 2 BACKGROUND

## 2.1 Introduction to China soybean market

China is one of the largest soybean consuming countries in the world. It consumed more than one third of the global supply in the last five years. Counterintuitively, this large agricultural nation has been satisfying its huge demand for soybeans by import.

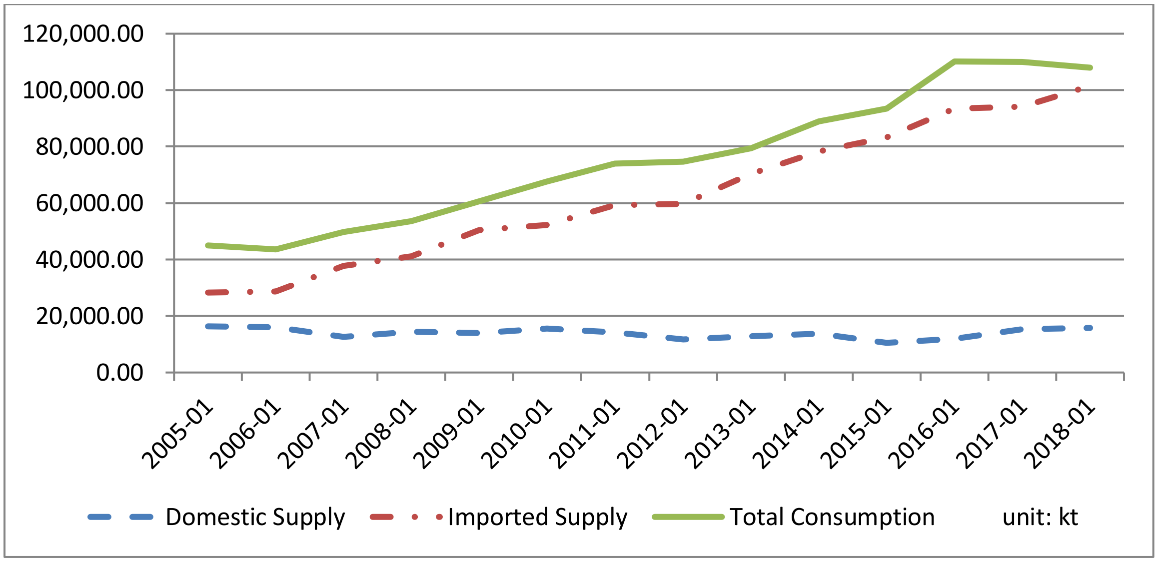


Figure 12: import level of China

As can be seen from the graph above, domestic annual soybeans supply in China has never been greater than 20 million tons since 2005, but the demand for soybeans has skyrocketed from 45 million tons in 2005 to 108 million tons in 2018. Clearly, most of the demand was met by importing soybeans. Imported soybeans has taken up more and more of the quantity in China's in total supply, reaching 94% in 2018 as compared with 63% in 2005. It is reasonable to conclude that the soybean market in China is mostly supported by imports, and that the soybean price in China will be largely affected by the imported soybean price.

This pattern can be explained by the comparative advantage theory which we introduced before. Given the domestic produced soybean price and the imported soybean price from January 1st, 2016 to February 15th, 2019, we can see that domestic soybean price has been higher than the imported soybean price. To make sure the relationship is robust, both domestic price and imported price are averaged based on the prices at different ports.

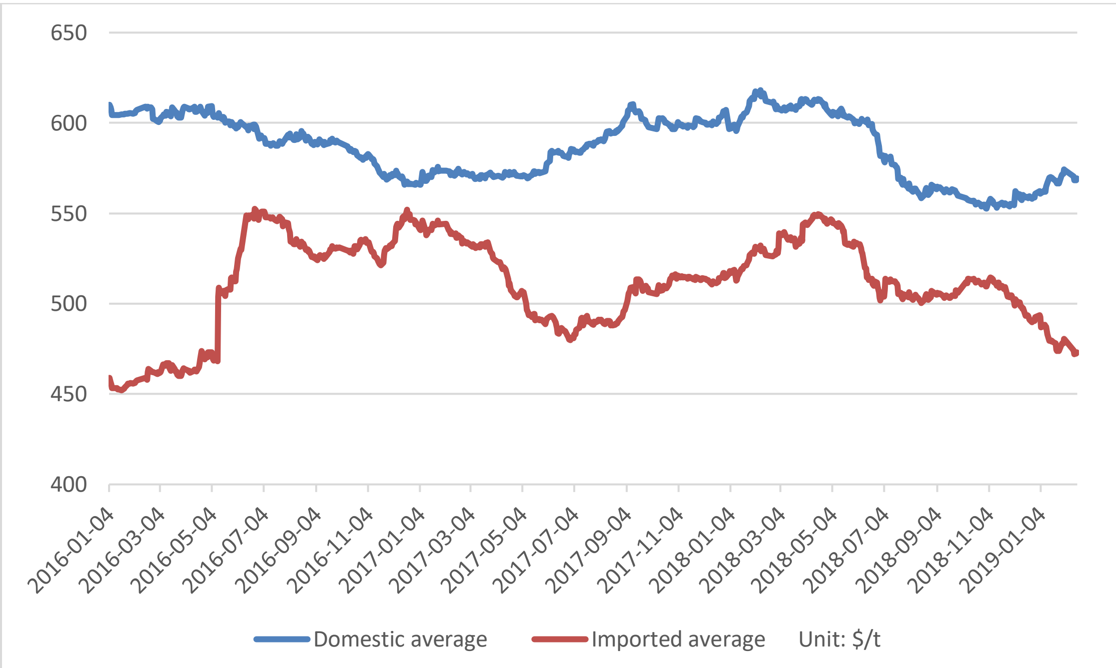


Figure 13: average soybean price

Apply this relationship to what we have discussed before and holding the other factors constant, we can draw a similar graph shows below. The slope of two curves can be derived as:

$$\frac{Q_1}{Q_2} = \frac{L_1/P_1}{L_2/P_2}$$

As domestic soybean price is much higher, the value $P_1$ is higher for domestic curve than that in international trading curve. So, the slope for domestic curve is flatter.

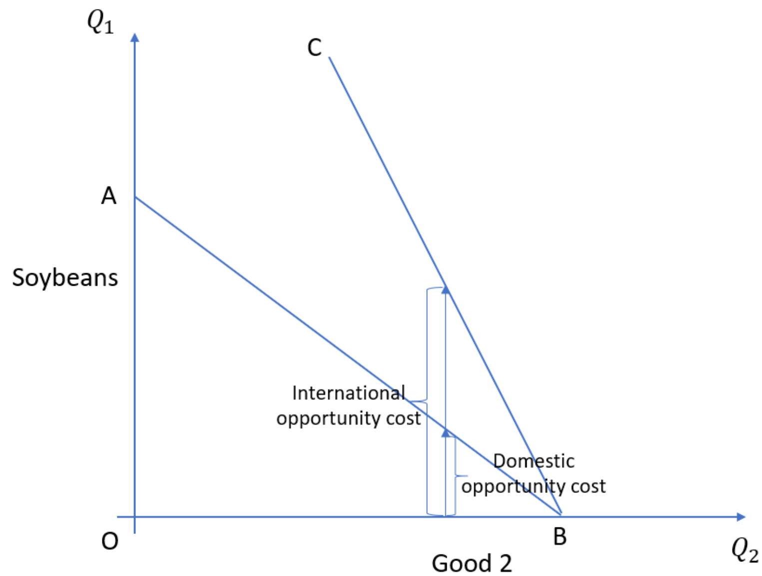


Figure 14: comparative advantage for soybean

As shown in the above graph, when one more unit of good 2 is produced domestically, the opportunity cost measured by soybeans is denoted as "domestic opportunity cost." If the extra unit of good 2 is not exported, the opportunity cost measured by soybeans is denoted as "international opportunity cost." Apparently, the production and export of good 2 can be exchanged for more soybeans than by producing soybeans domestically.

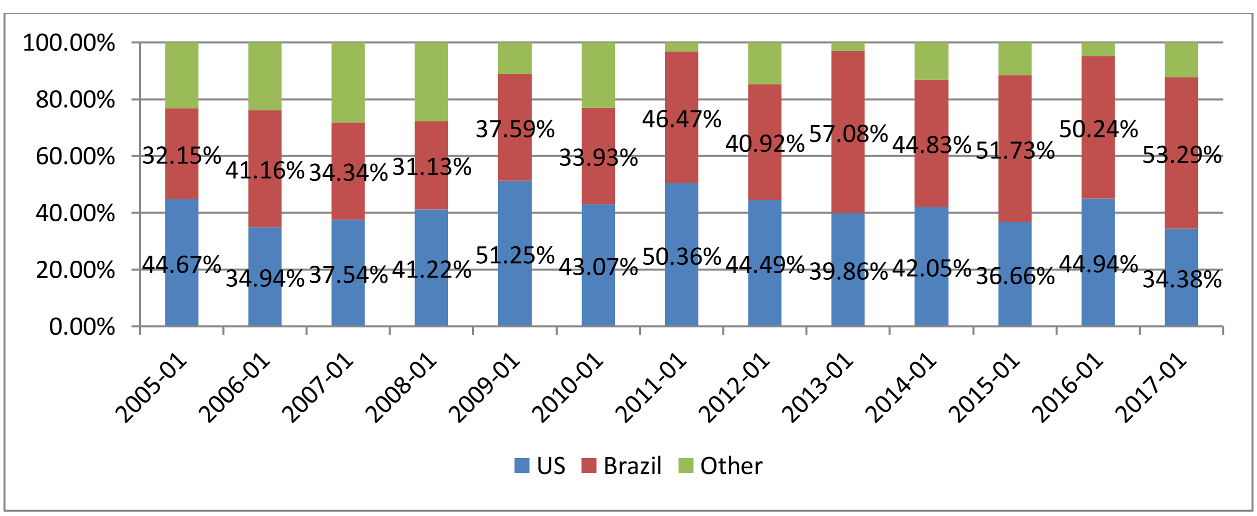

Figure 15: distribution of import

There is no doubt that soybean import trade is of great significance to China's soybean market. Thus, we need to understand the import business in China. There are two main countries from which China imports soybeans: Brazil and the US. These two countries account for more than 80% soybeans importing volume. This concentration of suppliers makes soybean supply in China highly dependent on trade conditions with Brazil and the US. For its US suppliers, China once received more than 50% of its total imported soybeans. Although the percentage has decreased in recent years, it still accounts for more than 34% of China's imported supply. Based on previous studies, if the US declared a trade war with China, then the soybean supply in China would become vulnerable, because it is unrealistic to expect to find an alternative supply to meet the huge demand in such a short time.

The United States is one of the largest soybeans exporting countries in the world, and most of its export is to China. During the past 13 years, of the soybeans China has consumed, between 32% to 72% was imported from the US. In recent years, the percentage has remained at about 55%, more than the rest of the world together. It is easy to see that China being is the largest purchaser of US soybeans, the demand and supply condition in China is likely to have a significant effect on the soybean market in the US. In order to make sure the US soybean market can sell at a decent price, one of the most efficient strategies would be to build up a long-term and friendly trading partnership with China.

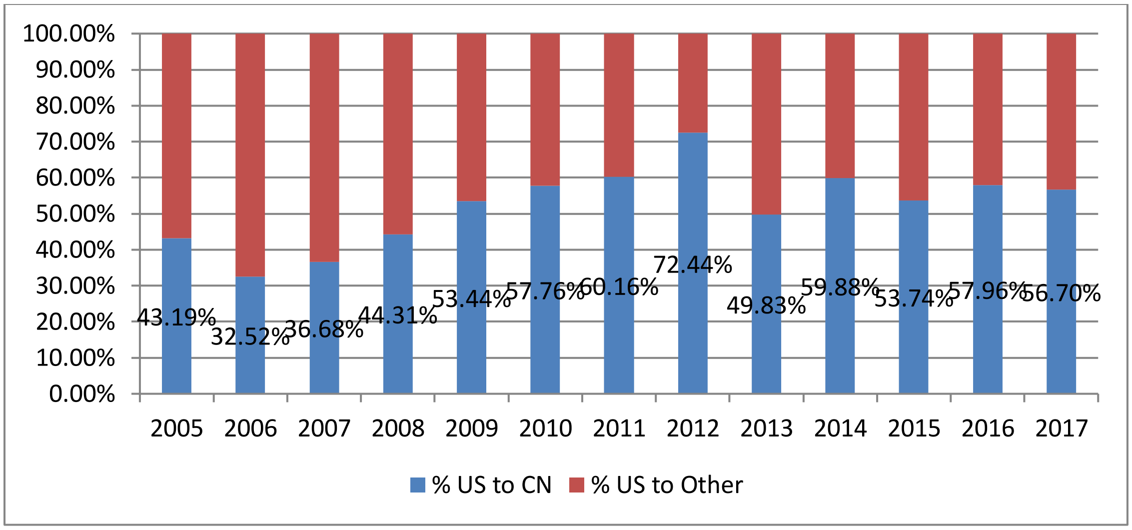


Figure 16: US export volume---to China

To sum up, it is apparent that both US and China should rely on each other to maintain healthy international trading conditions and a stable soybean market. Without soybeans from the US, there would be a huge gap between supply and demand in China that it could not be filled in a short time; which, in turn, could force the soybean price to rise dramatically. The rising price would probably result in a slow-down of other soybean-related markets in China, such as oil production and soybean meal. At the same time, those soybeans that were not shipped to China would likely be dumped on the US domestic market, and either cause the price to crash or just perish in storage. (Zhou, Y., Baylis, K., Coppess, J., & Xie, Q. 2018). No matter which happens, farmers' income will be eaten up. In order to avoid lose-lose situation, both nations worked hard in previous years, trying to eliminate trade frictions, which included lowering tariffs and increasing import quotas. However, this friendly trading situation was broken by president Donald Trump when he declared a trade war with China in 2018.

Looking at the import mechanism in detail, as shown below, we can observe an interesting pattern in soybean imports. China has been importing soybeans alternately from US and Brazil in alternate months. This is largely due to geographical and seasonal reasons. From the graph, we can conclude that the import level from the US usually peaks in December and reaches its low in July. The import cycle for Brazil, opposite to that of the US, reaches its peak in June or July and falls to its lowest level in December or January.

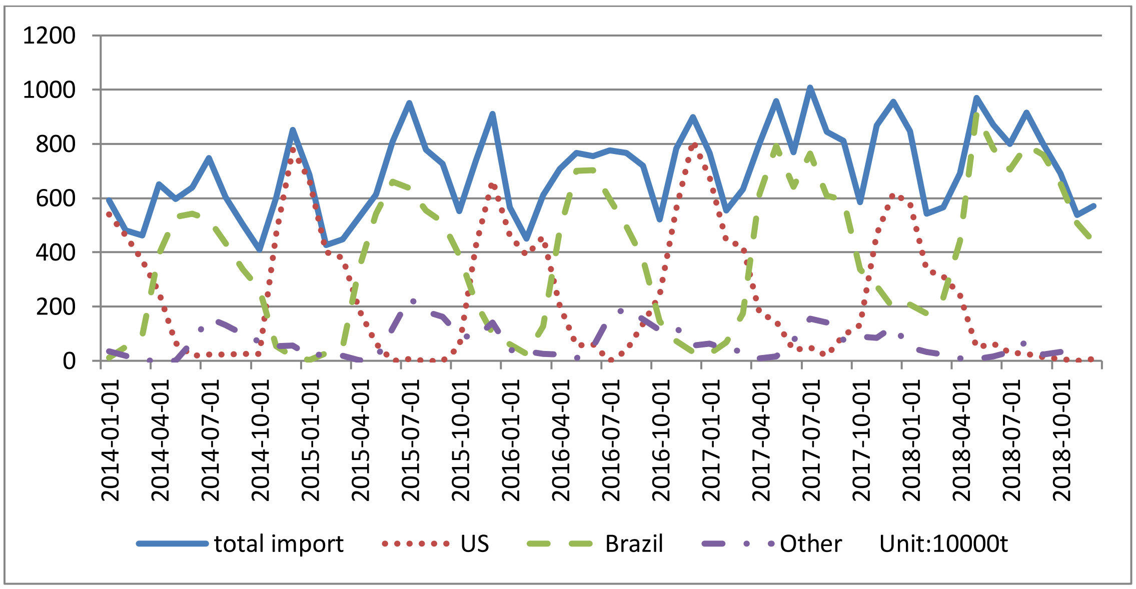


Figure 17: import volume of China from US and Brazil

Not surprisingly, after the trade war began, China nearly stopped importing from the US. After this, the import level from the US still decreased before July as usual, but did not reverse and increase thereafter.

The import volume from Brazil has kept to the same pattern as before. It follows the periodical cycle and its peak level has been increasing year by year. Although the import level soared in May, when China announced to revenge retaliation, it reverted back to its normal pattern in the months thereafter and the level started to decrease. For other import countries, there has not been any significant climb in import volume. To sum up, the one-time supply boom from Brazil in May 2018 was only likely to support total demand in China for a few months. Because during this period, typically from May to September, the demand is almost met by Brazil soybeans. However, if US soybeans were supposed to be the major fulfillment for domestic demand, the negative effect of the trade war would be exposed. This partially explains the increase in the Chinese soybean futures price from late June to October.

As shown below, the soybean futures price did not increase immediately; it even decreased after the declaration of an additional tariff, because increased Brazil soybean supply could still satisfy demand in the short term. However, starting in July, when the US supply was supposed to take the lead, the soybean futures price rocketed up as little soybean was imported from the US. The later downturn of the futures price, as one might notice, occurred much later than the announcement of retaliatory tariff and could have been caused by various other reasons including political and economic. That is another story and will not be covered in this paper. We can see that the trade war is somehow influencing the Chinese market, and that prices may reflect bad news about international trade.

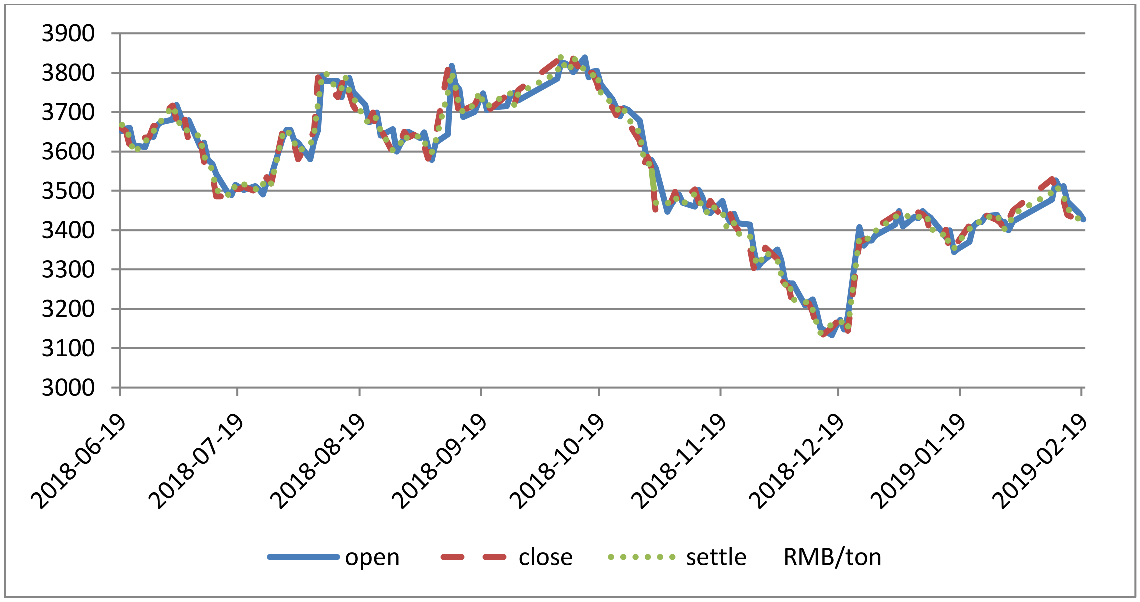


Figure 18: soybean futures price in Dalian Commodity Exchange

## 2.2 The big picture of underlying economy and trading conditions

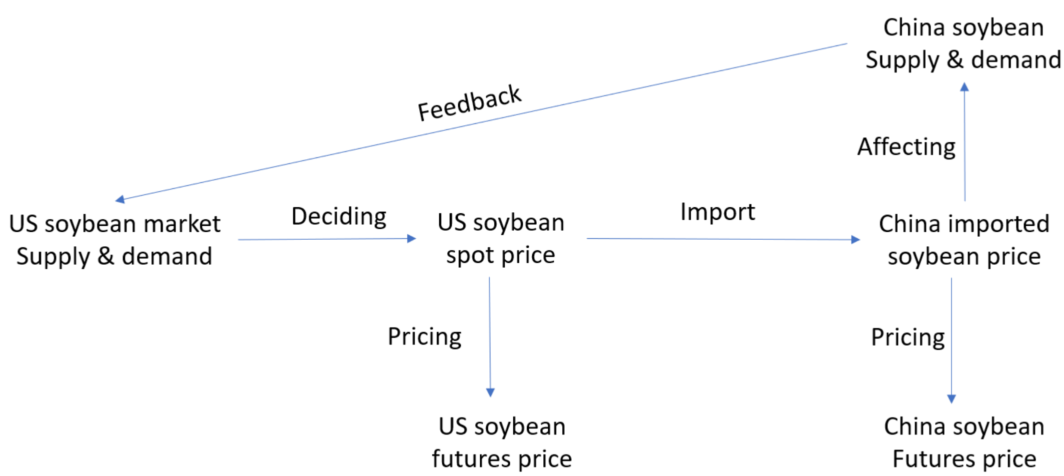


Figure 19: trade patterns between China and US

To further analyze how prices can reflect information across markets and the effect of a trade war, we constructed the above price signaling graph. Futures price, based on previous theories, is determined by underlying spot price. Spot price, according to classical economic models, is decided by supply and demand. Also, different markets and prices are linked by international trades between nations. Thus, in order to study the relationships between prices, we need first to understand how international trades are conducted and how the prices are determined.

Starting from the left side, we first look at the soybean market in the US. Domestically, US farmers will decide how much to produce based on the forecasted soybean demand, thus creating supply for the market. All the soybean supplies will be consumed either by domestic customers or by the rest of the world through export. In the end, the soybean market will be cleared at an equilibrium price. Next, for those soybeans that are ready to be shipped outside of US, exporters need to deliver soybeans to their assigned export ports. The equilibrium soybean price, plus the shipment cost from storage to the port and other costs before soybeans are loaded on vessels and leave the US, is called free on board, or FOB. The FOB price refers to the US soybean spot price in the above graph.

$$\text{FOB} = \text{local soybean price} + \text{costs before soybeans are loaded for export}$$

Before international trades get started, buyers and sellers will sit down and negotiate a trading price and other contract terms, including the FOB price. Specifically, in this paper, the two parties are the US as seller and China as buyer. There is a great geographical distance between the US and China, so the international shipment cost will cause the soybean price to rise after they are shipped to China. When these imported soybeans finally get distributed to Chinese market, the spot price will be the US spot price plus international shipment costs and tariffs, along with other related custom clearance costs. This price then is China’s imported soybean price.

$$\text{China imported soybean price} \\ = \text{FOB} + \text{international shipment cost} + \text{tariff} + \text{custom clearance fee}$$

After absorbing the imported soybeans, the Chinese domestic soybean market becomes complete. Imported supply plus Chinese-grown soybean supply is the total soybean supply in China. Since soybean supply in China is mainly provided through import, the soybean market price in China is kind of predetermined when buyers and sellers sign trading contracts. Thus, contrary to previous theories where equilibrium price is determined by interaction of supply and demand, the demand in China might now not be able to have a significant effect on price. What is more likely is that China's domestic demand will react to the pre-settled price. However, as China is the largest buyer of soybeans exported from the US, the demand for soybeans in China will be an important factor when US farmers make their planting forecast. How the Chinese market reacts to the price will probably be taken into consideration in the US, thereby influencing US soybean growing market.

Despite the underlying economic and trading conditions, there are also interactions between the spot price and the futures price. As discussed above, the futures price is determined mainly by the spot price.

$$\mathrm{F} = \mathrm{S} * e^{rt}$$

Where F is the futures price, S refers to spot price, r is risk free rate or other referencing rate, t is the maturity for a futures contract. Apparently, there is frequent interaction between the futures price and the spot price. This relationship applies to both the US and Chinese futures markets.

To sum up, the US spot price for soybean could influence both the US soybean futures price and the Chinese soybean spot price (and Chinese spot price is used to determine Chinese futures price). Since the four prices are related directly or indirectly, it is our objective to find out if there is any relationship between these prices, and, if so, do they still exist after a trade war.

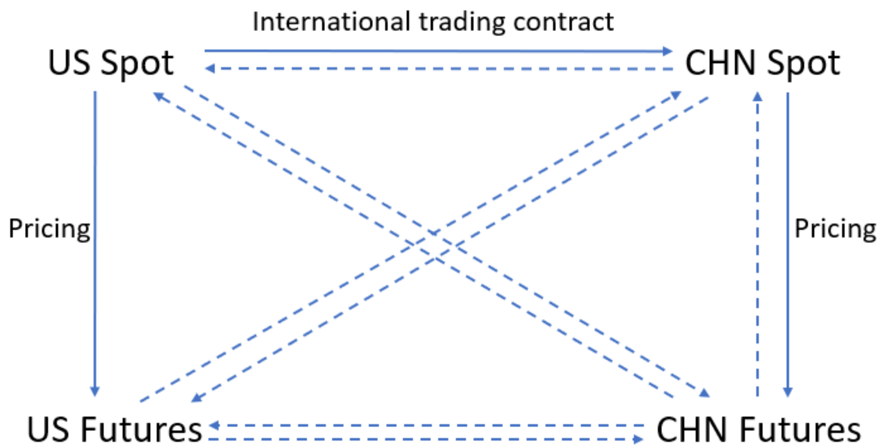


Figure 20: hypotheses about price signaling

The above graph shows the big picture in terms of price part. The solid lines refer to relationships already known from previous theories. The dotted lines are hypothetical relationships that we think might exist. As discussed above, futures price is determined by spot price. But futures price, according to its nature, is a kind of spot price, except that it is determined in a period of time before the spot date occurs. When investors enter into contracts at prices they prefer, their underlying assumption is that the belief that the price is to their benefit. Thus, the futures price might be able to reflect investor perspectives in terms of future price performance. This phenomenon is called price discovery, in which the futures price is a guidance to price movement in the future. If this holds true, will the futures price influence the current spot price to move towards it? Based on this, we draw influential effect.

## 2.3 Hypothesis

Since China is the largest buyer of US soybeans, customers in China will look closely at the US soybean price in order to manage material cost and do their budgeting in advance. As the US futures price reflects the spot price in the future, it is highly possible that Chinese customers will take the former into consideration when negotiating contract price with US sellers. Thus, there might be relationship between the US futures price and the Chinese spot price.

Following the same logic of this relationship between futures price and spot price, the Chinese futures price also reflects the consensus of spot price in the future. As US farmers decide how much soybean to produce, they might want to look at future Chinese demand by studying the expected future price. If the futures price rises a lot, they may want to produce more and to profit; if the futures price exhibits backwardation, they might cut the production volume to avoid loss. The change in supply will affect the spot price in the US. In sum, there might be relationship between Chinese futures price and US spot price.

It is certain that China and US markets are actively interacting with each; therefore, it is reasonable to assume that the futures market in both countries also reflects this interaction. However, unlike previous studies, which focused mainly on the settlement prices or closing prices in the two markets, the relationship between the futures markets will not be fully discovered until we comprehensively understand the patterns and prices of these markets.

Due to time difference between the two countries, the Chinese futures market and the US futures market are not trading simultaneously. The trades for soybean futures on the Chicago Board of Trade (CBOT) are typically executed from 8:30 am to 1:20 pm. This time period is not a trading window for China. In China, the Dalian Commodity Exchange (DCE) is open from 9:00 am to 3:00 pm, during which period the exchange accepts and matches orders for soybean futures. All this happens while US traders are sleeping.

Let's start with the US futures market. When a trading day ends for CBOT, there is a closing price for that day. The price will not move until the next trading day. During this period, the DCE market opens, and before the market starts trading, there will be a few minutes for traders to shout their prices for either long or short positions. The DCE will try to match long and short orders according to certain rules and finally will arrive at the opening price. After one day's trading, the closing price is reported and the market closes. Then, a few hours later, the CBOT market opens again, and the opening price will be determined similar to how it is done by the DCE market. Since the two markets trade in a sequential order, traders will look at the performance in the other country and make their own trading strategies for the day, which could build relationships between prices and markets.

Unlike previous studies, which focused mainly on closing prices or settlement prices and attempted to discover their relationships, this paper studies this issue based on these previous studies but by expanding them in more detail. As discussed above, the relationship between the Chinese market and the US market might not be fully revealed by using just closing prices. Instead, the relationship should be like a circle, with time difference incorporated, as in the graph below:

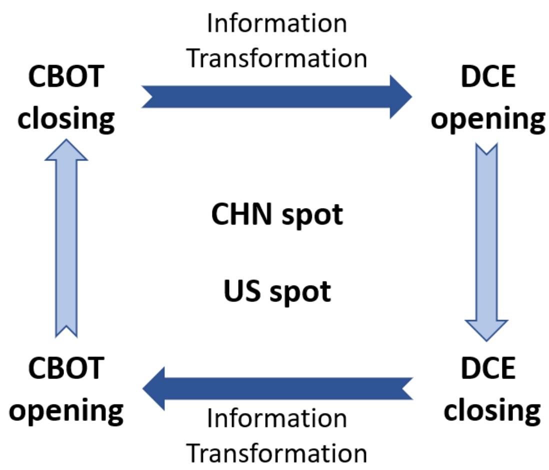


Figure 21: possible relationship between US and China markets

In this paper, we will address this issue by looking at different price pairs according to sequence of time. The following pairs are what we will study about:

1. CBOT closing price and DCE opening price
2. DCE closing price and CBOT opening price
3. Chinese spot price and both futures prices
4. US spot price and both futures prices

As we discussed above, had China and US maintained a healthy trading partnership, the soybean markets in both countries should have been operated as usually expected. However, in June 2018, the US declared a trade war against China, and the situation deteriorated.

In August 2017, the US government initiated a Section 301 investigation under Trade Act of 1974 on imported goods, for the purpose of detecting and punishing trade partners who were involved in unfair trading activities. Although this investigation was said to apply to many countries that trade with the US, China was the actual target, according to later analysis.

From January to March 2018, the Unites States announced additional tariffs on steel, aluminum, and some industrial accessories imported from China. But these were just expressive of trade frictions and were not really part of a trade war (because they counted for only a small portion of total trading volume).

However, the situation became worse on March 22, 2018, when the US government announced additional tariffs on 50 billion dollars of goods from China. A month later, a detailed list made public showed a further 25% tariff would be imposed on more than 1,330 categories of goods, totaling 50 billion dollars.

To fight back, the Chinese government held a pressing conference on April 4, 2018, at which it announced the imposition of an additional 25% tariffs on 106 kinds of products imported from US. The detailed list from June 15, 2018 included soybeans. This is the time period in which soybean trade was involved in a trade war.

After the trade war began, the overall picture we discussed above was ruined. The direct impact caused trading conditions to deteriorate.

According to the formula given by China Customs, the tariff imposed on imported soybean applies to ad valorem tax and can be calculated as:

$$\mathrm{T} = P_{pretax} * tax\ rate$$

Thus, the imported soybean price after tax will be:

$$P_{after\ tax} = P_{pretax} * (1 + tax\ rate)$$

Before the trade war, China imposed 3% tax rate on soybean imported from US. After the avenging tax rate was imposed, the new imported price will be higher:

$$P_{after\ tax} = P_{pretax} * (1 + tax\ rate + 25\%)$$

We can compare the tax and price before and after trade war with the help of the graph below:

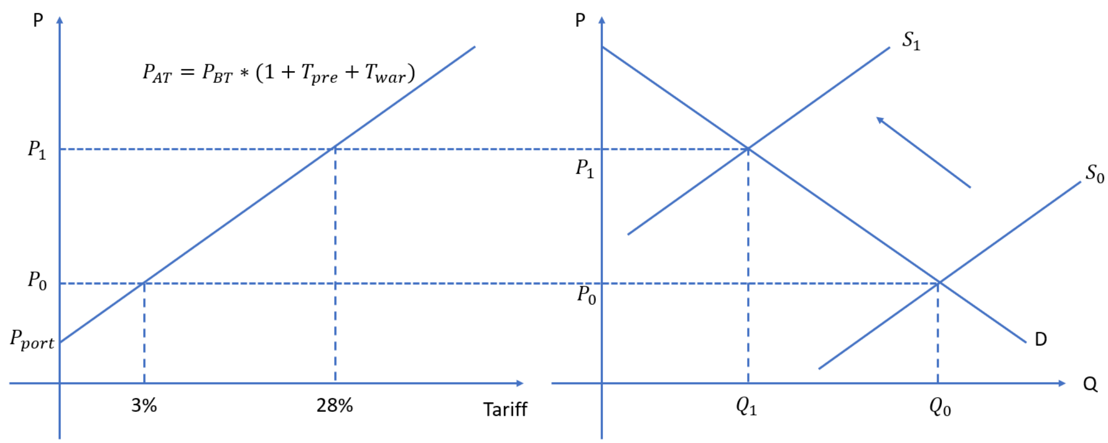


Figure 22: tariff effect on supply

The left side of the graph visualizes the relationship between the imported soybean price and the tariff level. The linear function crosses the vertical axis at $P_{port}$, which is the imported soybean price before tax, also the FOB price in the US plus shipment cost from the US to China and other related costs. Before the trade war, when soybeans arrived at any port in China, Chinese Customs would charge a tax, raising the price up to $P_0$. At this price level, China's domestic market could absorb $Q_0$ soybeans and maintain an equilibrium. However, as China imposed an extra 25% tariff on imported soybeans, it was difficult for buyers and sellers to negotiate alternative contract terms, which could then adversely affect the trading volume between the two countries. Import volume would decline and supply decrease to $Q_1$. In the future, the supply level could decrease even more if the Chinese government decided to retaliate for a longer period. In order to meet the previous demand of $Q_0$, China needed to find alternative resources or to tolerate the high price. This is why China imported more soybeans from Brazil and lowered its tax rate to zero for some other Asian countries, hoping to maintain enough import volume and support domestic demand.

Due to the additional tax, the import volume from the US decreased and the relationship between the US soybean spot price and China's soybean spot price might no longer exist, and futures prices might diverge between the two markets. Ultimately, the price relationship between China and the US might disappear.

In sum, what we are mainly focusing on is the price relationships. Before the trade war began, we assume there existed relationships between soybean prices in the US and China, both spot and futures prices. But, in our view, after the trade war, the relationship no longer exists.

# CHAPTER 3 METHODOLOGY

As previously stated, our purpose to study price relationships between CBOT, DCE and spot markets, both before and after declaration of the China-US trade war. Specifically, we want to discover how signaling effect is transferred between China and the US, as well as between futures and spot markets. Previous studies have shown that an effective and commonly used method to address this issue is to analyze past price movements of the three markets simultaneously. Price signaling is considered to exist if the lagged price performance of one or more variables is influencing the future price movement of another.

Based on this premise and these data properties, we need a model that not only can estimate multiple time series variables simultaneously but also capture variable interactions as time progresses, which leads to the Vector Autoregression Model (VAR). The VAR model, however, is a statistical model which requires little economic basis. Thus, in order to provide convincing evidence of causal relationships among prices in different markets, we need to conduct further tests; and this is where the Granger Causality Test becomes useful.

## 3.1 VAR Model

As discussed above, VAR model is a generalized univariate autoregressive model allowing time series variables to be estimated simultaneously as a combined system. It captures intertemporal effect among variables, making it a desired model to study causality effect. A general VAR model with p lags can be denoted as VAR(p) in following formula:

$$\boldsymbol{y_t} = \boldsymbol{\alpha} + \boldsymbol{\beta_1} * \boldsymbol{y_{t-1}} + \boldsymbol{\beta_2} * \boldsymbol{y_{t-2}} + \cdots + \boldsymbol{\beta_p} * \boldsymbol{y_{t-p}} + \boldsymbol{\varepsilon_t}$$

$\boldsymbol{y}$ refers to an $n * 1$ matrix of dependent variables $y_i$, values of variables are collected as $y_{i,t}$ where i is the variable order and t is for time. Written as:

$$\boldsymbol{y_t} = \begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \dots \\ y_{n,t} \end{bmatrix}$$

Similarly, $\boldsymbol{y_{t-i}}$ refers to same data structure except that $\boldsymbol{y_{t-i}}$ matrix is lagged by i period and serve as independent variables. $\boldsymbol{\alpha}$ and $\boldsymbol{\beta_i}$ are coefficient matrices to be estimated, $\boldsymbol{\varepsilon_t}$ represents error term matrix. An illustrative example of a three-variable VAR model with one lag is shown below:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \\ y_{3,t} \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} + \ [\beta_1 \ \beta_2 \ \beta_3] \ \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \\ y_{3,t-1} \end{bmatrix} + \ \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{bmatrix}$$

Which is equivalent to:

$$y_{1,t} = \ \alpha_1 + \ \beta_{1,1} * y_{1,t-1} + \beta_{1,2} * y_{2,t-1} + \beta_{1,3} * y_{3,t-1} + \ \varepsilon_{1,t}$$

$$y_{2,t} = \ \alpha_2 + \ \beta_{2,1} * y_{1,t-1} + \beta_{2,2} * y_{2,t-1} + \beta_{2,3} * y_{3,t-1} + \ \varepsilon_{2,t}$$

$$y_{3,t} = \ \alpha_3 + \ \beta_{3,1} * y_{1,t-1} + \beta_{3,2} * y_{2,t-1} + \beta_{3,3} * y_{3,t-1} + \ \varepsilon_{3,t}$$

In the above example, each variable in the combined system is estimated using lags of itself and the other two variables. If the estimation of any coefficient in β is significant under a chosen significance level, then the variable is possibly a cause of a dependent variable. The estimating model can be expanded by including more lags if needed. Changing lag order, however, could bring estimation problems if not conducted properly. We will discuss this in later sections.

Our discussion focuses mainly on three-time series: the soybean futures price in the CBOT, soybean futures price in the DCE, and soybean spot price in China. In order to be precise, we use either the opening or closing price rather than just the settlement price when testing causality effect. Intuitively, the number of lag periods to be included should be one. However, for the purpose of conducting a steady and valid estimation, lag order will be determined after conducting certain tests.

One can expand the VAR model in various ways. It is supported in VAR model to include exogenous variables and time factor, as well as more lags. Flexible as it seems, the VAR model still has requirements and assumptions to be satisfied before it exhibits steadiness and uncovers relationships of time series data. Typically, the data used for VAR model should be stationary, the test for stationarity will be discussed later. Besides, there are three assumptions imposed for error term:

$\mathrm{E}\left[\varepsilon_{i,t}\right] = 0$: every error term has zero mean

$\mathrm{E}\left[\varepsilon_{i,t}, \varepsilon'_{i,t}\right] = \Omega$: covariance matrix for same period error terms is $\Omega$,

$\mathrm{E}\left[\varepsilon_{i,t}, \varepsilon'_{i,t-k}\right] = 0$: there is no serial correlation in error terms

To sum up, these assumptions make sure that variables in the system are indeed affecting each other, and that the VAR model includes all the relative independent variables so that there is no important information left in error terms.

Another important step before conducting VAR estimation is to find out proper lag order. We basically want to include all lags that exhibit predicting power while excluding lags that show no effect on dependent variables. Unfortunately, there is no consensus on how to choose optimal lag order. What is universally agreed is that different selection criteria should be used together, and that for empirical research one should use the lag order that results in a well-behaved residual (zero mean, no serial correlation). This paper uses STATA as the estimation environment, which provides five kinds of criteria: likelihood ratio (LR), final prediction error (FPE), Akaike's Information Criterion (AIC), Hannan-Quinn Information Criterion (HQIC), and Bayesian information criterion (SBIC). It is rational to use them all and to choose the lag order preferred by most of the criteria.

To make sure the VAR model is set appropriately, it is important to conduct several tests about data, assumptions and steadiness.

### 3.2 Dickey-Fuller Test

The Dickey-Fuller test is mainly used to verify the stationarity of data. As discussed previously, the VAR model requires data to be stationary. Stationarity refers to data properties including trendless, constant mean, and variance over time, as well as constant autocorrelation structure. Non-stationary data might result in an overfitting problem in estimations which results in misleading conclusions.

In practice, the Dickey-Fuller test is constructed to detect the unit root. A unit root, to some extent, is a concept opposite to that of stationarity. The existence of a unit root will cause problems in detecting inferences from a time series model. Simply stated, if a time series has a unit root, then it is not stationary.

The mechanism of the Dickey-Fuller test is as follows. First, the time series data can be written as:

$$y_t = \rho * y_{t-1} + \mu_t$$

Where $y_t$ is the variable of interest, $\rho$ is the coefficient of lagged data, and $\mu_t$ refers to error term. Note that the value of $\rho$ here is very important in determining the nature of the time series. If $\rho$ has value of 1, then it indicates the series has a unit root. Based on this, one can easily rewrite the function by subtracting lag for each side:

$$y_t - y_{t-1} = \Delta y_t = (\rho - 1) * y_{t-1} + \mu_t = \gamma * y_{t-1} + \mu_t$$

Now the Dickey-Fuller test, instead of testing whether $\rho$ equals to one, is testing whether $\gamma$ is zero. The hypothesis test is set as below:

$$H_0: \gamma = 0, indicating\ the\ existence\ of\ a\ unit\ root, data\ is\ non-stationary$$

$$H_1: \gamma \neq 0, indicating\ no\ existence\ of\ unit\ root, reject\ non-stationarity\ of\ data$$

Comparing the p-value with the significance level specified at the beginning, one can comes with the result of either reject or fail to reject the null hypothesis.

However, seldom does time series data exhibit stationarity. To deal with it, a widely used solution is to take first difference of original data before further study. Our approach is to adopt a traditional way to avoid non-stationarity by taking log difference.

3.3 Serial correlation test for residual.

In the assumption part, it is emphasized that the error term in the VAR model should not be serial correlated. To detect serial correlation, we use a prevailing method called the Lagrange Multiplier Test. Simply stated, this test is basically maximizing the likelihood function using the Lagrange Multiplier, and then constructing a statistic to test whether the current parameter satisfies the optimized function.

For an objective likelihood function $L(\theta)$ with constraint $g(\theta) = C$, one can construct a Lagrange function using Lagrange multiplier $\lambda$ as follows:

$$L = logL(\theta) + \lambda(g(\theta) - C)$$

The next step is to take the first order condition and solve the function:

$$L' = \frac{\partial \, log \, L(\theta)}{\partial \theta} + g'(\theta) * \lambda = 0$$

If the current parameter $\theta_0$ already satisfies optimization condition or close enough, then the original log-likelihood function value should not change too much after being optimized, which also means the constraint imposed has little effect on optimization, thus $\lambda$ should be close to 0. From here, one can conduct an equivalent test $H_0: \lambda = 0$.

Apply this method in previous VAR model example, we have the following steps to test serial correlation between error terms. First, conduct VAR estimation and get estimated coefficients of each independent variable, then calculate estimated value of dependent variables. For each variable, we will get an estimated value as follows:

$$\widehat{y_{1,t}} = \widehat{\alpha_1} + \widehat{\beta_{1,1}} * y_{1,t-1} + \widehat{\beta_{1,2}} * y_{2,t-1} + \widehat{\beta_{1,3}} * y_{3,t-1}$$

$$\widehat{y_{2,t}} = \widehat{\alpha_2} + \widehat{\beta_{2,1}} * y_{1,t-1} + \widehat{\beta_{2,2}} * y_{2,t-1} + \widehat{\beta_{2,3}} * y_{3,t-1}$$

$$\widehat{y_{3,t}} = \widehat{\alpha_3} + \widehat{\beta_{3,1}} * y_{1,t-1} + \widehat{\beta_{3,2}} * y_{2,t-1} + \widehat{\beta_{3,3}} * y_{3,t-1}$$

Note that the estimated value has no error term. Next, comparing estimated value with true value of the variable, and calculate the value of error term:

$$\widehat{\varepsilon_{1,t}} = y_{1,t} - \widehat{y_{1,t}}$$

$$\widehat{\varepsilon_{2,t}} = y_{2,t} - \widehat{y_{2,t}}$$

$$\widehat{\varepsilon_{3,t}} = y_{3,t} - \widehat{y_{3,t}}$$

Third, notice that the estimation function can be written as:

$$\varepsilon_{1,t} = y_{1,t} - \alpha_1 - \beta_{1,1} * y_{1,t-1} - \beta_{1,2} * y_{2,t-1} - \beta_{1,3} * y_{3,t-1}$$

$$\varepsilon_{2,t} = y_{2,t} - \alpha_2 - \beta_{2,1} * y_{1,t-1} - \beta_{2,2} * y_{2,t-1} - \beta_{2,3} * y_{3,t-1}$$

$$\varepsilon_{3,t} = y_{3,t} - \alpha_3 - \beta_{3,1} * y_{1,t-1} - \beta_{3,2} * y_{2,t-1} - \beta_{3,3} * y_{3,t-1}$$

Now we set $\varepsilon_{i,t} = \widehat{\varepsilon_{i,t}}$ as constraint just like previously described $\mathrm{g}(\theta) = C$ and estimate three functions above, we will get the estimate of variance-covariance matrix Σ, denoted as $\hat{\Sigma}$.

Fourth, to test serial correlation, we add lags to above estimations and result in the following:

$$\widehat{\varepsilon_{1,t}} = \eta_1 + \phi_{1,1} * y_{1,t-1} + \phi_{1,2} * y_{2,t-1} + \phi_{1,3} * y_{3,t-1} + \rho_{1,j} * \widehat{\varepsilon_{1,t-j}} + v_{1,t}$$

$$\widehat{\varepsilon_{2,t}} = \eta_2 + \phi_{2,1} * y_{1,t-1} + \phi_{2,2} * y_{2,t-1} + \phi_{2,3} * y_{3,t-1} + \rho_{2,j} * \widehat{\varepsilon_{2,t-j}} + v_{2,t}$$

$$\widehat{\varepsilon_{3,t}} = \eta_3 + \phi_{3,1} * y_{1,t-1} + \phi_{3,2} * y_{2,t-1} + \phi_{3,3} * y_{3,t-1} + \rho_{3,j} * \widehat{\varepsilon_{3,t-j}} + v_{3,t}$$

Now we have updated estimate of variance-covariance matrix, $\tilde{\Sigma}$.

Finally, the test statistic can be constructed to be:

$$LM = (T - d - 0.5) * ln(\frac{\hat{\Sigma}}{\tilde{\Sigma}})$$

Where T is the number of observations in VAR model, d is the number of coefficients estimated in the fourth step. Such mathematical transformation makes the LM statistic asymptotically distributed with $\chi^2$.

Intuitively, given the same sample size, if errors are not serial correlated, then the significance test for $\rho_{i,j}$ should fail, and $\hat{\Sigma}$ should be close to $\tilde{\Sigma}$, which makes LM value close to 0. Based on chosen significance level, we can decide whether error terms exhibit serial correlation.

3.4 Granger Causality Test

As discussed before, the VAR model is more like a statistical model that requires little economic theory for estimation. In order to find convincing evidence to prove the existence of causality effect or information transfer between markets, the Granger Causality test is always applied together with VAR estimation. The causality relationship here refers to two properties: first, the cause happens prior to the effect; second, the cause has unique information about the future values of effect. These two properties can be summarized by the following inequality:

$$P(X_{t+1} \subseteq S|I(t)) \neq P(X_{t+1} \subseteq S|I_{-Y}(t))$$

Given past data of time series Y, the probability of future value of X falling into a non-empty set is different from that probability when Y is unknown.

Practically speaking, the method of conducting granger test is also a kind of significance test. For example, if we want to test whether lags of variable X granger cause Y, there are three steps to do: first, using information criterion such as AIC and SBIC to determine lag order for the following estimation functions:

$$y_{i,t} = \alpha_i + \beta_{i,1} * y_{i,t-1} + \cdots + \beta_{i,p} * y_{i,t-p} + \varepsilon_{i,t}$$

$$y_{i,t} = \alpha_i + \beta_{i,1} * y_{i,t-1} + \cdots + \beta_{i,p} * y_{i,t-p} + \beta_{j,1} * y_{j,t-1} + \beta_{j,q} * y_{j,t-q} + \varepsilon_{ij,t}$$

Note that the second estimation is similar to the first one, only adding lags of another variable.

Second, check if the predicting power of the second function is higher than that of the first one. Also, conduct F-test for coefficients of added variable. If the second function has higher predicting power and the F-test is significant under chosen level, it is highly possible that the added variable granger causes the dependent variable.

Granger test for VAR model is a multivariate test with the number of variables and lags included already specified in VAR model. For example, a VAR model with three variables and two lags can be written as:

$$y_{1,t} = \beta_{1,1} * y_{1,t-1} + \beta_{1,1-} * y_{1,t-2} + \beta_{1,2} * y_{2,t-1} + \beta_{1,2-} * y_{2,t-2} + \beta_{1,3} * y_{3,t-1} + \beta_{1,3-} * y_{3,t-2}$$

$$y_{2,t} = \beta_{2,1} * y_{1,t-1} + \beta_{2,1-} * y_{1,t-2} + \beta_{2,2} * y_{2,t-1} + \beta_{2,2-} * y_{2,t-2} + \beta_{2,3} * y_{3,t-1} + \beta_{2,3-} * y_{3,t-2}$$

$$y_{3,t} = \beta_{3,1} * y_{1,t-1} + \beta_{3,1-} * y_{1,t-2} + \beta_{3,2} * y_{2,t-1} + \beta_{3,2-} * y_{2,t-2} + \beta_{3,3} * y_{3,t-1} + \beta_{3,3-} * y_{3,t-2}$$

For each dependent variable above, we first run an autoregression and then gradually add other variables into the estimation. If we observe that the predicting power increases as a new variable is added in, then it is highly possible that the newly added variable Granger-causes the dependent variable.

## 3.5 Eigenvalue test

For any VAR model, coefficient estimation is not the only procedure. We still need to test the stability of the results. The test of stability verifies whether the results reflect true reality or just happen coincidently. Stability generally refers to the robustness of estimation results. If the model gives the same results after a little disturbance is added, one can conclude the existence of robustness. A simple example, the example of predator and prey, can be applied here to illustrate the concept of stability.

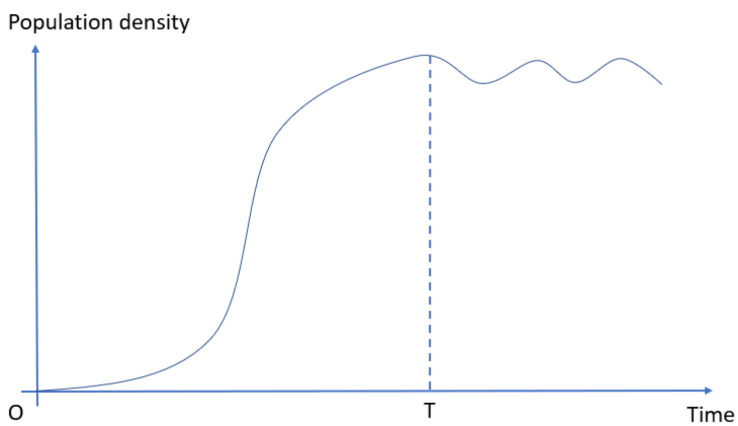


Figure 23: predator and prey example

As shown above, the population density of any species basically follows the pattern as time evolves. Begin from time 0, the population first increases dramatically. Then at time T, the population becomes mature and the density will remain at a certain level, with little fluctuations. To see the steady period, we often refer to first order condition of a function. The population growth rate, which is the slope of the curve, is shown below:

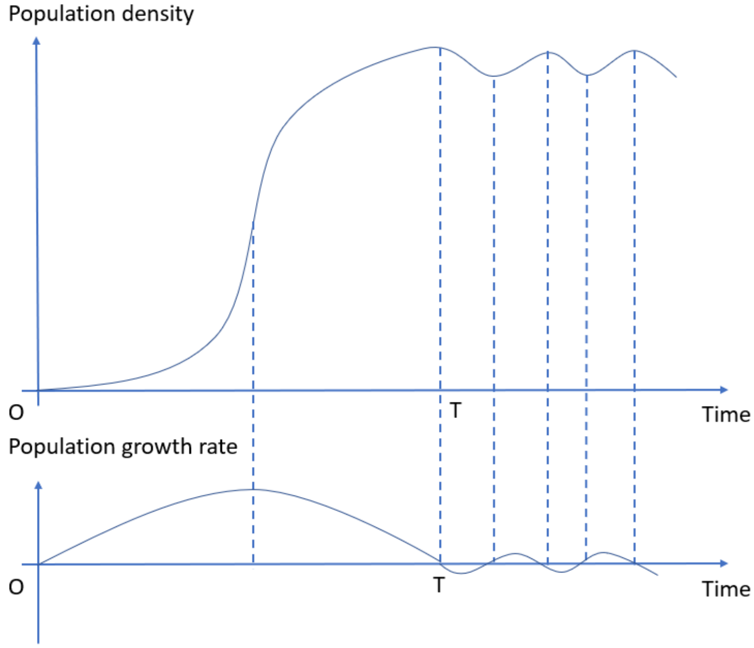


Figure 24: steady state illustration

When population growth rate reaches 0, it might indicate a steady period where population remains at certain level. Just like time after T, when population density is at a high level, the growth rate turns to negative and drags down population density; when population density is relatively low, the growth rate turns positive and density increases. However, zero growth rate does not necessarily mean a steady period. At time 0, the growth rate is zero, but after a little disturbance, population density starts to increase and never reverses back. So, zero growth rate at time 0 is just a coincidence and is not stable.

Similarly, a stability test for the VAR model applies this method with respect to matrix. For example, a VAR model with 2 lags can be written as:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \\ y_{3,t} \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} + [\beta_1\ \beta_2\ \beta_3] \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \\ y_{3,t-1} \end{bmatrix} + [\beta_{1-}\ \beta_{2-}\ \beta_{3-}] \begin{bmatrix} y_{1,t-2} \\ y_{2,t-2} \\ y_{3,t-2} \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{bmatrix}$$

We can rewrite it into:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \\ y_{3,t} \end{bmatrix} = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix} + \ [b_1 \ b_2 \ b_3] \ \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \\ y_{3,t-1} \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ e_3 \end{bmatrix}$$

$$\begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \\ y_{3,t-1} \end{bmatrix} = \begin{bmatrix} a_{1-} \\ a_{2-} \\ a_{3-} \end{bmatrix} + \ [b_{1-} \ b_{2-} \ b_{3-}] \ \begin{bmatrix} y_{1,t-2} \\ y_{2,t-2} \\ y_{3,t-2} \end{bmatrix} + \begin{bmatrix} e_{1-} \\ e_{2-} \\ e_{3-} \end{bmatrix}$$

To be simple, rewrite above two matrices into:

$$\begin{bmatrix} Y_t \\ Y_{t-1} \end{bmatrix} = \begin{bmatrix} A_1 & A_2 \\ I & 0 \end{bmatrix} * \begin{bmatrix} Y_{t-1} \\ Y_{t-2} \end{bmatrix} + \begin{bmatrix} \varepsilon_t \\ 0 \end{bmatrix}$$

After the estimation, the matrices above finally become:

$$\widehat{Y_t} = \hat{A}\widehat{Y_{t-1}} + \widehat{\varepsilon_t}$$

As we discussed above, steady period for a single variable can be found by equaling first order derivative to 0. The value of the variable remains at certain level for small disturbance. For a vector, this concept is adapted that the vector does not change direction after multiplying by another vector. In our example, this concept means:

$$mK = \hat{A}K$$

$$m\begin{bmatrix} K_1 \\ K_2 \end{bmatrix} = \begin{bmatrix} A_1 & A_2 \\ I & 0 \end{bmatrix} * \begin{bmatrix} K_1 \\ K_2 \end{bmatrix}$$

Where m refers to a real number, K is the objective vector. After multiplying by a vector $\hat{A}$, the vector K remains at its original direction, only changes in length. If this equation is satisfied, then vector, or the coefficient matrix could be stable. Then next step is to check eigenvalues. Rewrite the matrix above, we have:

$$mK_1 = A_1K_1 + A_2K_2$$

$$mK_2 = K_1$$

Substitute $K_2$ with $K_1$:

$$mK_1 = A_1K_1 + \frac{A_2K_1}{m}$$

$$K_1 = \frac{A_1K_1}{m} + \frac{A_2K_1}{m^2}$$

Eigenvalues are roots of:

$$[I - A_1m^{-1} - A_2m^{-2}] = 0$$

For vectors, we determine stability by comparing results with unit circle. This is intuitive because any coefficient greater than 1 indicates an explosive trend. Apparently, If all eigenvalues lie inside the unit circle, the results are stable.

# CHAPTER 4 RESULTS AND DISCUSSION

## 4.1 Data

Previous studies focus mainly on closing prices of the US and Chinese futures markets when studying related issues, to discover the price relationships between two prices. We apply this method in a more detailed way and focus on four prices. We focus on soybean futures prices and spot prices for both the US and Chinese markets. The data collected includes opening price, closing price and settlement price of both markets, CBOT and DCE (soybean #1 futures contract). Spot prices of the two countries are also collected for the study of price linkage. For the purpose of robustness, we collected the Chinese soybean spot price from three major ports of importation, Port of Qingdao, Shanghai, and Nantong. We also gathered three US soybean spot prices from three major soybean producing locations: Kansas, Illinois, and Iowa. We also collected data from the USD-CNY exchange rate for further use.

All the time series were collected from the WIND database, which is a good data source for Chinese data and some international data. The US time series data, like CBOT prices and spot price, were double checked with CME group and Bloomberg. All the time series were collected from January 4, 2016 to February 14, 2019, including periods both before and after the trade war. Due to difference in holiday periods in the two countries, there is some data from China that does not have corresponding data in US, and vice versa.

To address this problem, we used two methods. We first used linear interpolation to fill in single-day missing data. However, if data is missing for more than two successive days, we simply delete them for the purpose of accuracy. We also generated a copy of all

Chinese market data, with origin unit of RMB or RMB/ton, and transfer unit to USD or cent/bushel using USD-CNY exchange rate.

After applying these two methods, we have the following data series:

| Data pairs | Number of observations |
|---|---|
| Before trade war, CBOT close & DCE open | 597 |
| Before trade war, DCE close & CBOT open | 578 |
| Before trade war, settlement & spot | 583 |
| After trade war, CBOT close & DCE open | 159 |
| After trade war, DCE close & CBOT open | 155 |
| After trade war, settlement & spot | 161 |
| USD-CNY exchange rate | 765 |

Table 1: data description

During regressions, we use the log differences of prices series by taking log of original data and then subtract lagged data to get differences.

## 4.2 Framework

### 4.2.1 Effect of exchange rate

As the US market and the Chinese market have different quoting currencies, it is important to consider the possible effect on estimation results caused by fluctuation in the exchange rate. Typically, using the log difference of data would eliminate a unit inconsistency problem. However, mathematically speaking, using log difference is close to calculating the percentage change ratio of price. If quoted prices in the Chinese market are transferred into USD quotes, then the log difference we take measures not only the percentage change rate of price, but also percentage change in exchange rate.

Fortunately, this does no harm to estimations. Typically speaking, a trade war always comes with a crash of currency, and the exchange rate has an important effect on international trading. We then can conduct two pairs of estimation to separate the effect caused by the exchange rate.


Figure 25: USD-CNY exchange rate

The graph shown above is the CNY/USD rate from 4th, January 2016 to 15th, February 2019. During this period, US dollar first appreciated gradually and then depreciated moderately. After the declaration of trade war, US dollar rocketed up dramatically, eating up last 16 months' CNY appreciation within only 6 months. In the short period from May to November, US dollar appreciated more than 11% to nearly 7. This incredibly appreciation even triggered protection of CNY exchange rate by the State Administration of Foreign Exchange of China (SAFE).

Apparently, this sharp appreciation in US dollar would possibly change the price movement trend of Chinese market data when transferred into USD quotes. Since we are focusing on the effect on price relationships caused by trade war, it is important to conduct estimations with and without exchange rate effect, respectively.

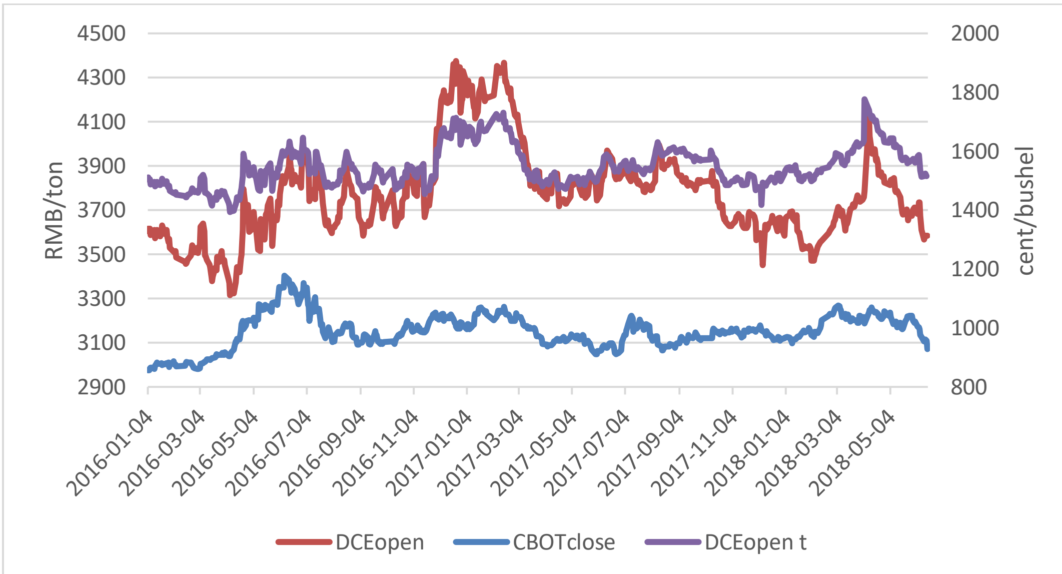


Figure 26: DCE soybean futures opening price, prewar

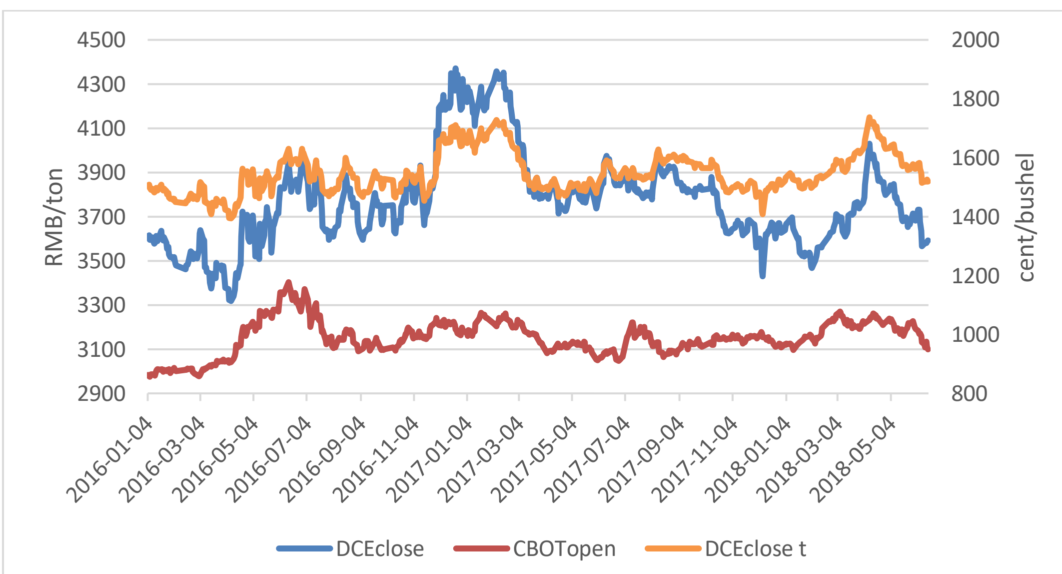


Figure 27: DCE soybean futures closing price, prewar

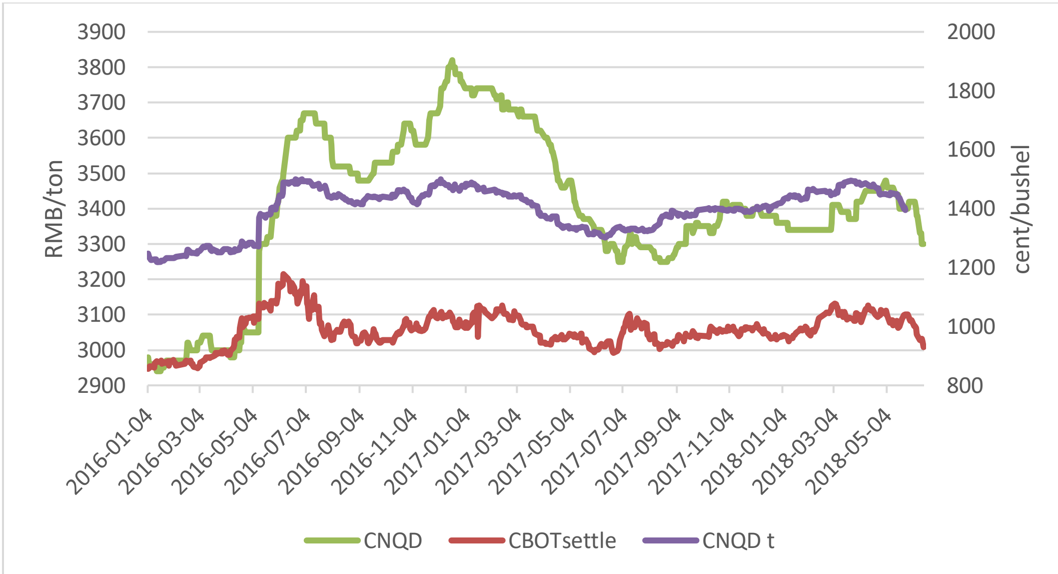


Figure 28: DCE soybean futures settlement price, prewar

The three graphs listed above show the Chinese market prices in both RMB/ton and cent/bushel. After transferring CNY quote to USD quotes, DCE prices and Chinese spot price change in values but keep the upward or downward trend.

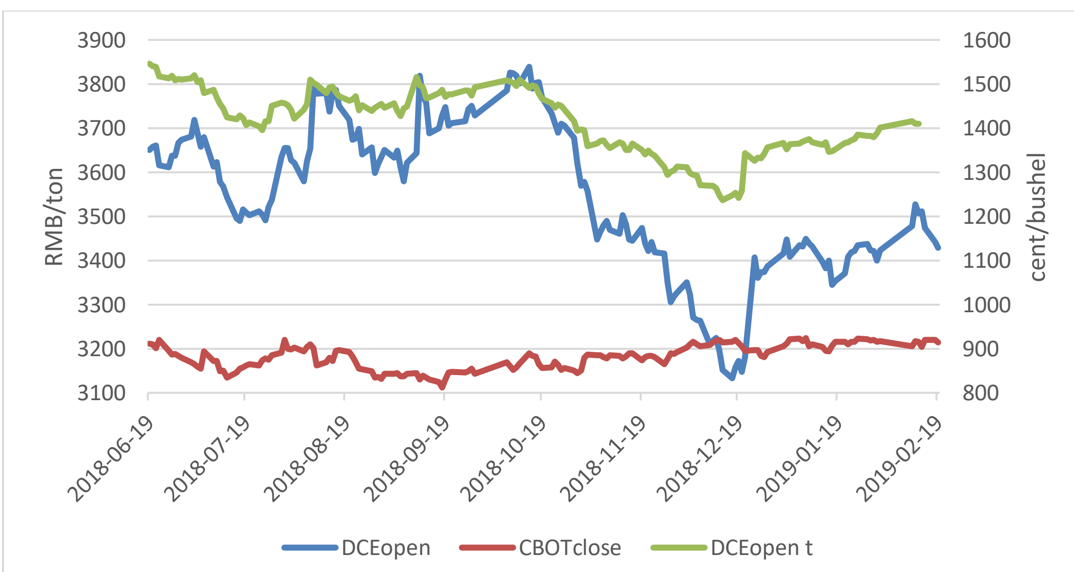


Figure 29: DCE soybean futures opening price, after war

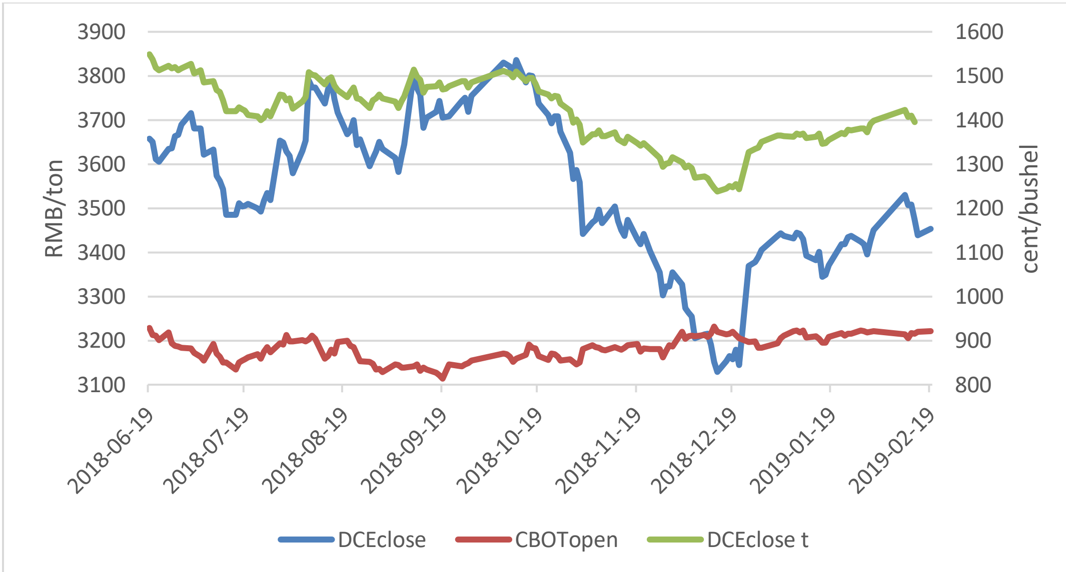


Figure 30: DCE soybean futures closing price, after war

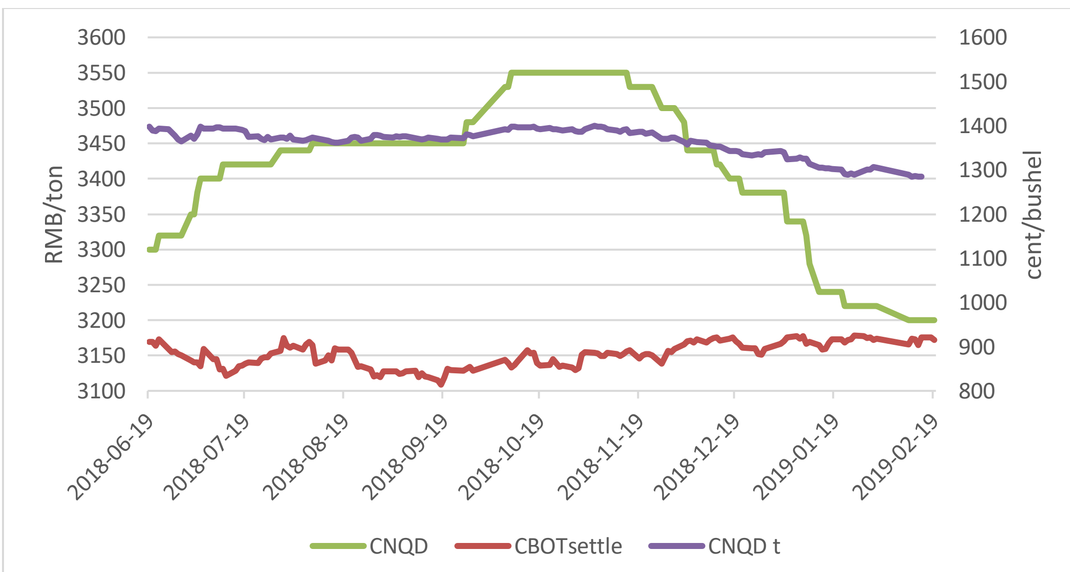


Figure 31: DCE soybean futures settlement price, after war

The above three graphs show the prices movement after the trade war, including Chinese prices quoted in RMB/ton and cent/bushel. Surprisingly, being affected by the exchange rate fluctuation, the USD quoted prices deviated a lot from original quoted prices for DCE opening and DCE closing respectively. For the Chinese spot price, the transferred prices even lose the original trend. Besides, during late June and early July in 2018, the trend for the DCE closing price and the DCE opening price both reversed from upward to downward after units' transfer. This reverse of trend is more significant for the spot price. Compared with what is was before the trade war, it is necessary to conduct estimations under different quoting currencies to discover the real relationship between prices.

### 4.2.2 Estimation process

The following graph shows the estimations we conducted. These estimations will uncover the overall effect on price relationship caused by the trade war and exchange rate, if any. To make sure of robustness, any estimations that include spot price, either Chinese spot or US spot, will be conducted three times. Remember that we have three Chinese spot prices coming from different ports and three US spot prices gathered from three soybean production sites. Within each estimation, we switch spot price once.

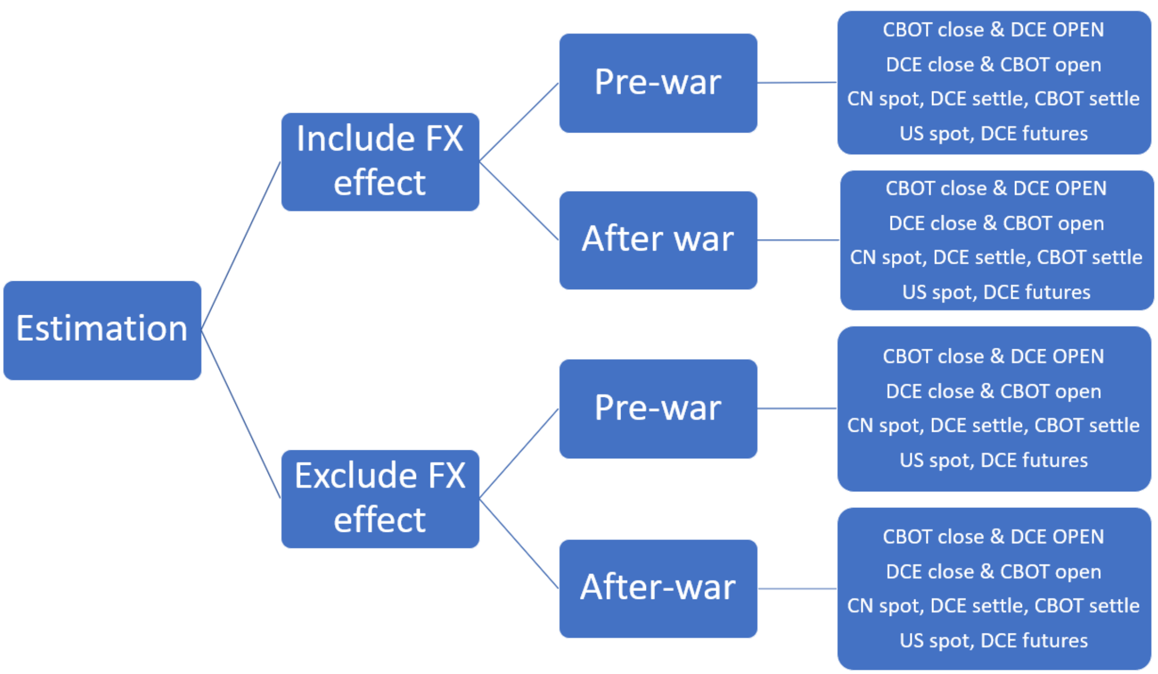


Figure 32: estimation pairs

## 4.3 Before the trade war, US futures, China futures and China spot

### 4.3.1 CBOT closing price, DCE opening price and Chinese spot

The estimation results are shown below:

```
Sample:  4 - 597                                  No. of obs      =       594
Log likelihood =  5972.985                        AIC             = -20.04035
FPE            =  3.97e-13                        HQIC            = -19.97995
Det(Sigma_ml)  =  3.70e-13                        SBIC            = -19.88526

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dlnCBOTclose          7     .011772   0.0071   4.276981   0.6392
dlnDCEopen            7     .011283   0.1284   87.51036   0.0000
dlnspot               7     .004692   0.1513   105.8933   0.0000
----------------------------------------------------------------
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dlnDCEopen   |
dlnCBOTclose |
         L1. |   .1914491   .0394096     4.86   0.000     .1142078    .2686905
         L2. |   .2414322    .042678     5.66   0.000     .1577848    .3250796
             |
  dlnDCEopen |
         L1. |  -.0806957   .0400429    -2.02   0.044    -.1591783   -.0022131
         L2. |  -.0961642    .039207    -2.45   0.014    -.1730085   -.0193199
             |
     dlnspot |
         L1. |    .256136   .0989242     2.59   0.010     .0622482    .4500238
         L2. |   -.101227   .0944952    -1.07   0.284    -.2864341    .0839801
             |
       _cons |  -.0001038    .000461    -0.23   0.822    -.0010074    .0007998
-------------+----------------------------------------------------------------
```

Table 2: estimation results for DCE opening price with CBOT closing price, prewar

The overall regression for log difference of the DCE opening price is significant at 1% level. Although we are focusing mainly on futures prices, we still add Chinese spot prices to make the model complete. Parameters show that for the estimation of the DCE opening price, both first and second lags of log difference of CBOT closing prices are significant under 1% level. Specifically, for each percentage increase in first lag day’s or second lag day’s CBOT closing price, there would be 0.19% and 0.24% increase in the next day’s DCE opening price respectively. It is highly possible that before the trade war, the CBOT closing price is a predicting variable of the DCE opening price. Lagged DCE opening prices are significant under 5% level; this is intuitive, as financial data is likely to exhibit momentum. Besides, lagged spot price is significant under 5% level, a weak indicator that each percentage increase in the previous day's spot price would result in 0.26% increase in the next day's DCE opening price.

| Equation | Excluded | chi2 | df | Prob > chi2 |
|---|---|---|---|---|
| dlnCBOTclose | dlnDCEopen | .51098 | 2 | 0.775 |
| dlnCBOTclose | dlnspot | 1.6509 | 2 | 0.438 |
| dlnCBOTclose | ALL | 2.3381 | 4 | 0.674 |
| dlnDCEopen | dlnCBOTclose | 54.499 | 2 | 0.000 |
| dlnDCEopen | dlnspot | 7.5665 | 2 | 0.023 |
| dlnDCEopen | ALL | 79.631 | 4 | 0.000 |
| dlnspot | dlnCBOTclose | 99.991 | 2 | 0.000 |
| dlnspot | dlnDCEopen | 4.6275 | 2 | 0.099 |
| dlnspot | ALL | 102.93 | 4 | 0.000 |

Table 3: granger causality test results for DCE opening price with CBOT closing price, prewar

To verify the VAR model result, we further conducted a Granger Causality test. Results show that CBOT closing price indeed Granger-causes the DCE opening price under 1% level. Spot price weakly Granger-causes the DCE opening price under 5% level.

### 4.3.2 DCE closing price, CBOT opening price and Chinese spot

| | | | |
|---|---|---|---|
| Sample: | 5 - 578 | No. of obs | = 574 |
| Log likelihood | = 5788.852 | AIC | = -20.09704 |
| FPE | = 3.75e-13 | HQIC | = -20.03493 |
| Det(Sigma_ml) | = 3.49e-13 | SBIC | = -19.9378 |

| Equation | Parms | RMSE | R-sq | chi2 | P>chi2 |
|---|---|---|---|---|---|
| ldlnCBOTopen | 7 | .01069 | 0.2226 | 164.3134 | 0.0000 |
| dlnDCEclose | 7 | .01137 | 0.0161 | 9.421452 | 0.1512 |
| dlnspot | 7 | .005185 | 0.0077 | 4.469328 | 0.6134 |

| | Coef. | Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| ldlnCBOTopen | | | | | | |
| ldlnCBOTopen | | | | | | |
| L1. | -.1123643 | .0414982 | -2.71 | 0.007 | -.1936993 | -.0310292 |
| L2. | .0362641 | .0372974 | 0.97 | 0.331 | -.0368375 | .1093657 |
| dlnDCEclose | | | | | | |
| L1. | .2715981 | .0407653 | 6.66 | 0.000 | .1916995 | .3514967 |
| L2. | .153957 | .042338 | 3.64 | 0.000 | .0709762 | .2369379 |

| | | | | | | |
|---|---|---|---|---|---|---|
| dlnspot | | | | | | |
| L1. | .6803404 | .0901476 | 7.55 | 0.000 | .5036544 | .8570264 |
| L2. | -.0643355 | .0945117 | -0.68 | 0.496 | -.249575 | .120904 |
| _cons | .000061 | .0004443 | 0.14 | 0.891 | -.0008098 | .0009319 |

Table 4: estimation results for DCE closing price, CBOT opening price, prewar

The overall regression for log difference of CBOT opening price is significant at 1% level. The spot price in China is also included for model completeness. Parameters show that for the estimation of the CBOT opening price, both first and second lags of log difference of the DCE closing prices are significant under 1% level. For each percentage increase in first and second order lag of the DCE closing price, there would be 0.27% and 0.15% increase in the following day's CBOT opening price respectively. It is highly possible that before the trade war, the DCE closing price is a predicting variable of CBOT opening price. The CBOT opening price itself shows possible predicting power under 1% level, reflecting momentum commonly seen in financial prices. Surprisingly, the lagged Chinese spot price of soybeans is also significant under 1% level, indicating its possible power to predict the CBOT opening price.

| Equation | Excluded | chi2 | df | Prob > chi2 |
|---|---|---|---|---|
| ldlnCBOTopen | dlnDCEclose | 59.787 | 2 | 0.000 |
| ldlnCBOTopen | dlnspot | 57.17 | 2 | 0.000 |
| ldlnCBOTopen | ALL | 161.19 | 4 | 0.000 |
| dlnDCEclose | ldlnCBOTopen | .34548 | 2 | 0.841 |
| dlnDCEclose | dlnspot | .75788 | 2 | 0.685 |
| dlnDCEclose | ALL | .9972 | 4 | 0.910 |
| dlnspot | ldlnCBOTopen | .73599 | 2 | 0.692 |
| dlnspot | dlnDCEclose | 1.8563 | 2 | 0.395 |
| dlnspot | ALL | 2.3914 | 4 | 0.664 |

Table 5: granger causality test results for DCE closing price, CBOT opening price, prewar

The Granger Causality Test verifies that both the Chinese spot price and the DCE closing price Granger-cause the CBOT opening price, before the start of the trade war.

### 4.3.3 CBOT settlement price, DCE settlement price and Chinese spot

```
Sample:  5 - 583                                    No. of obs      =       579
Log likelihood =    5866.6                          AIC             = -20.16097
FPE            =  3.52e-13                          HQIC            = -20.07286
Det(Sigma_ml)  =  3.18e-13                          SBIC            = -19.93499

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dlnCBOTsettle        10     .013247   0.0275   16.39199   0.0591
dlnDCEsettle         10     .009408   0.1421   95.90739   0.0000
dlnspot              10     .004962   0.0768   48.14117   0.0000
----------------------------------------------------------------
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dlnspot      |
dlnCBOTsettle |
          L1. |   .0954857   .0157695     6.06   0.000      .064578    .1263933
          L2. |   .0546533   .0169494     3.22   0.001      .021433    .0878735
          L3. |   .0257825   .0167484     1.54   0.124    -.0070437    .0586087
              |
 dlnDCEsettle |
          L1. |  -.0311484   .0230251    -1.35   0.176    -.0762768      .01398
          L2. |  -.0237187   .0231729    -1.02   0.306    -.0691366    .0216993
          L3. |  -.0103285   .0221371    -0.47   0.641    -.0537163    .0330594
              |
      dlnspot |
          L1. |   .0306392   .0437319     0.70   0.484    -.0550737    .1163521
          L2. |  -.0114407   .0434701    -0.26   0.792    -.0966406    .0737592
          L3. |   .0709762   .0430183     1.65   0.099    -.0133381    .1552906
              |
        _cons |   .0001742    .000205     0.85   0.395    -.0002276     .000576
------------------------------------------------------------------------------
```

Table 6: estimation results for settlement prices and Chinese spot, prewar

For the estimation for Chinese soybean spot price, we used settlement prices for both US and Chinese market instead of opening or closing prices, because settlement prices are used for delivery and are more related to spot prices. The regression for log difference of the Qingdao spot price is significant at 1% level. Parameters show that for the estimation of the Chinese soybean spot price, the first and second lag of log difference of CBOT settlement are significant; each percentage increase in first or second lag of CBOT settlement price would contribute to 0.10% and 0.05% increase in spot price. But DCE settlement is not helpful in prediction.

```
+------------------------------------------------------------------+
|          Equation           Excluded |   chi2     df Prob > chi2 |
```

| | | | | |
|---|---|---|---|---|
| dlnCBOTsettle | dlnDCEsettle | 5.1505 | 3 | 0.161 |
| dlnCBOTsettle | dlnspot | .82396 | 3 | 0.844 |
| dlnCBOTsettle | ALL | 5.5305 | 6 | 0.478 |
| dlnDCEsettle | dlnCBOTsettle | 58.244 | 3 | 0.000 |
| dlnDCEsettle | dlnspot | 8.1003 | 3 | 0.044 |
| dlnDCEsettle | ALL | 64.477 | 6 | 0.000 |
| dlnspot | dlnCBOTsettle | 42.119 | 3 | 0.000 |
| dlnspot | dlnDCEsettle | 3.7109 | 3 | 0.294 |
| dlnspot | ALL | 42.658 | 6 | 0.000 |

Table 7: granger causality test for settlement prices and Chinese spot, prewar

The Granger causality test supports the conclusion that the CBOT settlement price Granger-caused the Chinese soybean spot price, before the trade war started. However, another estimation indicates that the inverse relationship is not significant, which means the Chinese spot price has little effect on the CBOT settlement price.

It is necessary to clarify that the above result all use the Qingdao spot price as the Chinese spot price, and that all price units are unified in USD/bushel. For the purpose of robustness, we ran each estimation three times and changed the Chinese spot price from different ports each time to make sure the relationship we discovered is not random. Also, in order to eliminate the effect caused by a volatile exchange rate, we conducted all the above estimations again using Chinese prices quoted by RMB/ton. Results using the other two spot prices and transferred unit produced similar conclusions.

To make sure the models are set properly, we did eigenvalue test and Lagrange Multiplier test for each regression. All eigenvalues are less than 1, indicating steadiness of models. All Lagrange Multiplier tests fail to reject the null hypothesis, so we cannot reject the null that there is no serial correlation between error terms. Thus, we are confident that the model assumption is met for each regression.

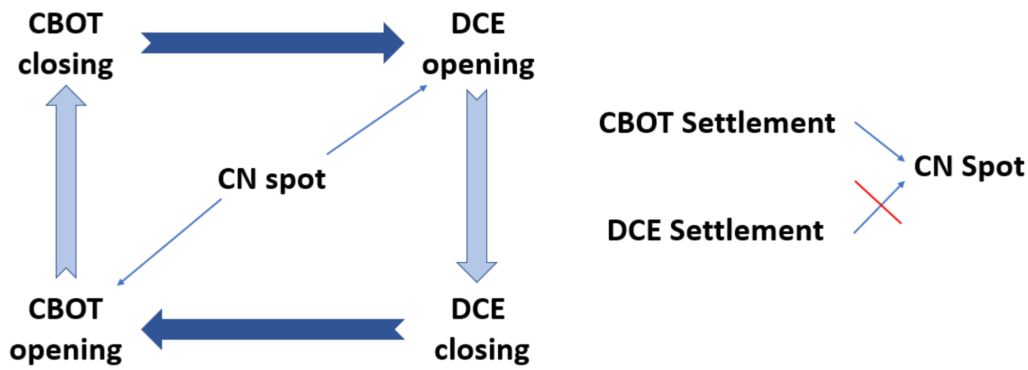


Figure 33: estimated price relationships before trade war

From the above estimations, we can conclude that before the start of the trade war, the Chinese futures market and the US futures market interacted with each other in a circular way. The CBOT closing price would affect the next day's DCE opening price, and the DCE closing price had an effect on the following day's CBOT opening price. The Chinese soybean spot price exhibited predicting power about both the DCE opening price and the CBOT opening price.

For prediction of the Chinese spot price, the results are a little bit counterintuitive. The previously prevailing idea that the Chinese futures price has a guiding effect on spot price is not significant in our analysis. But the US futures settlement price does have significant effect on the Chinese spot price.

## 4.4 After the trade war, US futures, China futures and China spot

As we have discussed above, after the trade war started, the price relationships that had existed before might disappear. To verify our hypothesis, we conduct the following estimations using same data as above but with time period starting after trade war.

### 4.4.1 CBOT closing price, DCE opening price and spot price

```
Sample:  600 - 756                                   No. of obs      =       157
```

```
Log likelihood =  1607.491                        AIC             = -20.32473
FPE            =  2.99e-13                        HQIC            = -20.22986
Det(Sigma_ml)  =  2.57e-13                        SBIC            = -20.09113

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dlnCBOTclose          4     .012161   0.0137   2.173677   0.5372
dlnDCEopen            4     .011075   0.0004   .0690777   0.9953
dlnspot               4      .00391   0.0042   .6544733   0.8839
----------------------------------------------------------------
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dlnDCEopen   |
dlnCBOTclose |
         L1. |   .0014865   .0724443     0.02   0.984    -.1405017    .1434748
             |
  dlnDCEopen |
         L1. |  -.0047171   .0797827    -0.06   0.953    -.1610884    .1516542
             |
     dlnspot |
         L1. |  -.0571176   .2244693    -0.25   0.799    -.4970693    .3828341
             |
       _cons |  -.0005965   .0008817    -0.68   0.499    -.0023247    .0011317
-------------+----------------------------------------------------------------
```

Table 8: estimation results for DCE opening price with CBOT closing price, after war

Not surprisingly, the estimation for the DCE opening price is no longer significant, and the lag of the CBOT closing price is not able to infer the DCE opening price anymore. The relationship between the CBOT closing price and the DCE opening price, as we discovered before, no longer exists. Another shocking result is that the Chinese spot price also loses its predicting power relative to the DCE opening price, which might indicate that trade war could even sever the price relationship within the Chinese spot and futures markets.

```
+------------------------------------------------------------------+
|          Equation           Excluded |   chi2     df Prob > chi2 |
|--------------------------------------+---------------------------|
|      dlnCBOTclose         dlnDCEopen |  .43329     1    0.510    |
|      dlnCBOTclose            dlnspot |  .50132     1    0.479    |
|      dlnCBOTclose                ALL |  .92164     2    0.631    |
|--------------------------------------+---------------------------|
|        dlnDCEopen       dlnCBOTclose |  .00042     1    0.984    |
|        dlnDCEopen            dlnspot |  .06475     1    0.799    |
|        dlnDCEopen                ALL |  .06515     2    0.968    |
|--------------------------------------+---------------------------|
|           dlnspot       dlnCBOTclose |  .28156     1    0.596    |
|           dlnspot         dlnDCEopen |  .00174     1    0.967    |
|           dlnspot                ALL |   .2832     2    0.868    |
+------------------------------------------------------------------+
```

Table 9: granger causality test for DCE opening price with CBOT closing price, after war

The granger test also fails, indicating no causality relationship between CBOT closing price and DCE opening price, nor Chinese spot price between DCE opening price.

### 4.4.2 DCE closing price, CBOT opening price and spot price

```
Sample:  582 - 733                                No. of obs      =       152
Log likelihood =  1543.121                        AIC             = -20.14633
FPE            =  3.57e-13                        HQIC            = -20.04936
Det(Sigma_ml)  =  3.05e-13                        SBIC            = -19.90761

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
ldlnCBOTopen          4     .012587   0.0465   7.416215   0.0598
dlnDCEclose           4      .01164   0.0102   1.566789   0.6669
dlnspot               4     .003978   0.0104    1.60361   0.6586
----------------------------------------------------------------
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ldlnCBOTopen |
ldlnCBOTopen |
         L1. |  -.1131643   .0791994    -1.43   0.153    -.2683922    .0420637
             |
 dlnDCEclose |
         L1. |   .1495054   .0884133     1.69   0.091    -.0237815    .3227923
             |
     dlnspot |
         L1. |   .3173953   .2584497     1.23   0.219    -.1891568    .8239474
             |
       _cons |   .0002574   .0010163     0.25   0.800    -.0017345    .0022492
-------------+----------------------------------------------------------------
```

Table 10: estimation results for DCE closing price and CBOT opening price, after war

Similarly, the estimation for the CBOT opening price is no longer significant under 1% level. No lag of DCE closing price predicts the CBOT opening price anymore. Intuitively, Chinese spot price also loses predicting power with respect to the CBOT opening price.

```
+------------------------------------------------------------------+
|          Equation           Excluded |   chi2     df Prob > chi2 |
|--------------------------------------+---------------------------|
|      ldlnCBOTopen        dlnDCEclose |  2.8594     1    0.091    |
|      ldlnCBOTopen            dlnspot |  1.5082     1    0.219    |
|      ldlnCBOTopen                ALL |  5.1425     2    0.076    |
|--------------------------------------+---------------------------|
|       dlnDCEclose       ldlnCBOTopen |  .05287     1    0.818    |
|       dlnDCEclose            dlnspot |  1.0255     1    0.311    |
|       dlnDCEclose                ALL |  1.0634     2    0.588    |
```

| | | | | |
|---|---|---|---|---|
| dlnspot | ldlnCBOTopen | .22512 | 1 | 0.635 |
| dlnspot | dlnDCEclose | .8907 | 1 | 0.345 |
| dlnspot | ALL | 1.0607 | 2 | 0.588 |

Table 11: granger causality test for DCE closing price and CBOT opening price, after war

The granger test fails again, confirming that the originally existed relationships between DCE closing price, Chinese spot price and CBOT opening price disappear.

### 4.4.3 DCE settlement price, CBOT settlement price and spot price

| | | | |
|---|---|---|---|
| Sample: | 586 - 744 | No. of obs | = 159 |
| Log likelihood | = 1659.232 | AIC | = -20.7199 |
| FPE | = 2.01e-13 | HQIC | = -20.62585 |
| Det(Sigma_ml) | = 1.73e-13 | SBIC | = -20.48829 |

| Equation | Parms | RMSE | R-sq | chi2 | P>chi2 |
|---|---|---|---|---|---|
| dlnCBOTsettle | 4 | .012338 | 0.0134 | 2.162058 | 0.5395 |
| dlnDCEsettle | 4 | .00957 | 0.0610 | 10.33701 | 0.0159 |
| dlnspot | 4 | .003709 | 0.0167 | 2.707456 | 0.4390 |

| | Coef. | Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| dlnspot | | | | | | |
| dlnCBOTsettle | | | | | | |
| L1. | .0190896 | .0237994 | 0.80 | 0.422 | -.0275564 | .0657357 |
| dlnDCEsettle | | | | | | |
| L1. | -.0395221 | .0301278 | -1.31 | 0.190 | -.0985716 | .0195274 |
| dlnspot | | | | | | |
| L1. | .0379079 | .0788452 | 0.48 | 0.631 | -.1166259 | .1924416 |
| _cons | -.0004985 | .0002937 | -1.70 | 0.090 | -.0010741 | .0000771 |

Table 12: estimation results for settlement prices and spot, after war

The estimation for the spot price is also insignificant and there is no lag of the CBOT settlement price exhibited predicting power on the Chinese spot price. The DCE settlement, same as in previous estimation, still has no effect on the Chinese spot price.

| Equation | Excluded | chi2 | df | Prob > chi2 |
|---|---|---|---|---|
| dlnCBOTsettle | dlnDCEsettle | .47555 | 1 | 0.490 |
| dlnCBOTsettle | dlnspot | .01523 | 1 | 0.902 |
| dlnCBOTsettle | ALL | .47686 | 2 | 0.788 |

| | | | | |
|---|---|---|---|---|
| dlnDCEsettle | dlnCBOTsettle | 7.3955 | 1 | 0.007 |
| dlnDCEsettle | dlnspot | .02935 | 1 | 0.864 |
| dlnDCEsettle | ALL | 7.4084 | 2 | 0.025 |
| dlnspot | dlnCBOTsettle | .64337 | 1 | 0.422 |
| dlnspot | dlnDCEsettle | 1.7209 | 1 | 0.190 |
| dlnspot | ALL | 2.6019 | 2 | 0.272 |

Table 13: granger causality test for settlement prices

The Granger test yet again failed: the previous existing relationship between the CBOT settlement price and the Chinese spot price no longer existed after the trade war started.

In order to make sure the estimations are robust, we estimated each price pair three times using different spot prices. We also performed the same analysis using all Chinese prices converted to US dollar quotes. The results are the same.

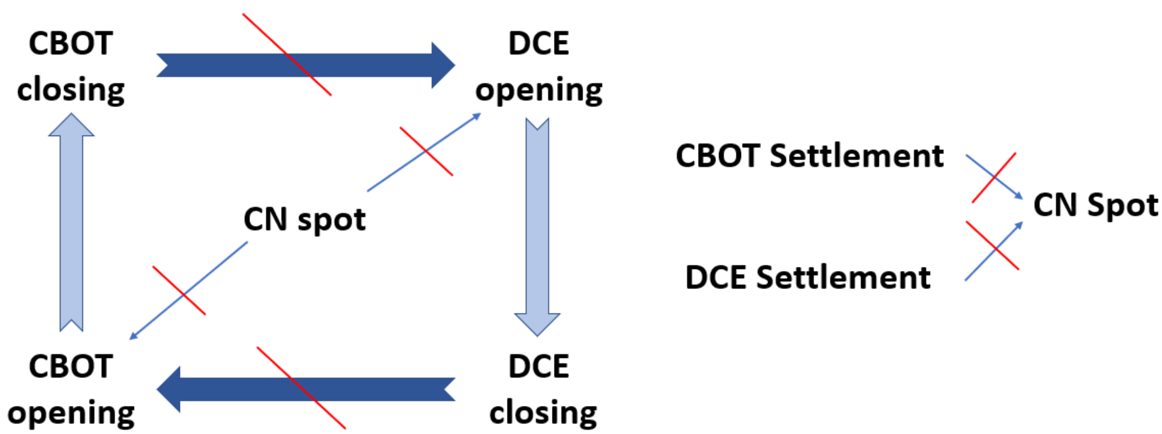


Figure 34: price relationships after trade war

After the trade war began, the previously existing relationships between two futures markets no longer existed, as the circulation was totally broken. The CBOT settlement price is cannot be inferred from the Chinese spot price, either. Simply stated, it is reasonable to conclude that a trade war can cause segmentation between the Chinese and

US futures markets and break the relationship between the US settlement price and the Chinese spot price.

As we discussed before, the US spot price may also play a role in price relationship. However, we cannot add it into the previous VAR estimation because of a multicollinearity problem. To address this problem, we conducted the following estimations, replacing US futures prices with the US spot price.

4.5 Before the trade war, US spot, China futures and spot

4.5.1 US spot, DCE opening price

```
Sample:  4 - 597                                    No. of obs      =       594
Log likelihood =   5956.02                          AIC             = -19.98323
FPE            =  4.21e-13                          HQIC            = -19.92283
Det(Sigma_ml)  =  3.92e-13                          SBIC            = -19.82814

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dlnUSKS               7     .012083   0.0025   1.477069   0.9610
dlnDCEopen            7      .01126   0.1320    90.3287   0.0000
dlnspot               7     .004711   0.1445   100.2932   0.0000
----------------------------------------------------------------
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dlnDCEopen   |
     dlnUSKS |
         L1. |     .19165   .0383299     5.00   0.000     .1165248    .2667752
         L2. |   .2385645   .0413475     5.77   0.000     .1575249    .3196042
             |
  dlnDCEopen |
         L1. |  -.0808448   .0400055    -2.02   0.043    -.1592541   -.0024355
         L2. |  -.0876238   .0391278    -2.24   0.025    -.1643128   -.0109348
             |
     dlnspot |
         L1. |   .2694031   .0981562     2.74   0.006     .0770205    .4617856
         L2. |  -.1044148   .0943256    -1.11   0.268    -.2892896    .0804599
             |
       _cons |  -.0000784     .00046    -0.17   0.865    -.0009801    .0008232
------------------------------------------------------------------------------
      +------------------------------------------------------------------+
      |          Equation           Excluded |   chi2     df Prob > chi2 |
      |--------------------------------------+---------------------------|
      |           dlnUSKS         dlnDCEopen |  .62454     2    0.732    |
      |           dlnUSKS            dlnspot |  .30222     2    0.860    |
      |           dlnUSKS                ALL |  1.0082     4    0.909    |
      |--------------------------------------+---------------------------|
      |        dlnDCEopen            dlnUSKS |  57.181     2    0.000    |
      |        dlnDCEopen            dlnspot |  8.4276     2    0.015    |
      |        dlnDCEopen                ALL |  82.417     4    0.000    |
      |--------------------------------------+---------------------------|
```

```
|           dlnspot             dlnUSKS |  94.438     2    0.000    |
|           dlnspot          dlnDCEopen |  3.8418     2    0.146    |
|           dlnspot                 ALL |  97.356     4    0.000    |
+-------------------------------------------------------------------+
```

Table 14: estimation results for US spot price and DCE opening price, prewar

Similar to previous results, to US spot price had predicting power with respect to the DCE opening price under 1% level. Each percentage increase in first or second lag of the US spot price results in a 0.19% and 0.24% increase in the DCE opening price.

### 4.5.2 US spot, DCE closing price

```
Sample:  4 - 578                                   No. of obs      =       575
Log likelihood =  5778.094                         AIC             = -20.05598
FPE            =  3.91e-13                         HQIC            = -20.02054
Det(Sigma_ml)  =  3.75e-13                         SBIC            = -19.96511

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
ldlnUSKS             4     .012011   0.0364   21.71404   0.0001
dlnDCEclose          4     .011408   0.0030   1.747146   0.6265
dlnspot              4     .005153   0.0149   8.668166   0.0340
----------------------------------------------------------------
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ldlnUSKS     |
    ldlnUSKS |
         L1. |   -.056118   .0446636    -1.26   0.209    -.1436569     .031421
             |
 dlnDCEclose |
         L1. |   .2171832   .0467251     4.65   0.000     .1256037    .3087627
             |
     dlnspot |
         L1. |  -.0937488   .1055149    -0.89   0.374    -.3005541    .1130566
             |
       _cons |   .0001455   .0004996     0.29   0.771    -.0008338    .0011248
-------------+----------------------------------------------------------------
      +-------------------------------------------------------------------+
      |          Equation           Excluded |   chi2     df Prob > chi2 |
      |--------------------------------------+----------------------------|
      |          ldlnUSKS        dlnDCEclose |  21.605     1    0.000    |
      |          ldlnUSKS            dlnspot |  .78941     1    0.374    |
      |          ldlnUSKS                ALL |  21.613     2    0.000    |
      |--------------------------------------+----------------------------|
      |       dlnDCEclose           ldlnUSKS |  .02744     1    0.868    |
      |       dlnDCEclose            dlnspot |  .76236     1    0.383    |
      |       dlnDCEclose                ALL |  .95797     2    0.619    |
      |--------------------------------------+----------------------------|
      |           dlnspot           ldlnUSKS |  4.8443     1    0.028    |
      |           dlnspot        dlnDCEclose |  .68284     1    0.409    |
      |           dlnspot                ALL |   6.521     2    0.038    |
      +-------------------------------------------------------------------+
```

Table 15: estimation results for US spot, DCE closing price, prewar

Similar to previous results, the DCE closing price had predicting power with respect to the US spot price under 1% level. However, the Chinese spot price had no effect on the US spot price.

### 4.5.3 US spot, Chinese spot price

```
Sample:  5 - 583                                     No. of obs      =       579
Log likelihood =  5945.155                           AIC             = -20.43231
FPE            =  2.68e-13                           HQIC            = -20.34421
Det(Sigma_ml)  =  2.42e-13                           SBIC            = -20.20634

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dlnUSKS              10     .012003   0.0112   6.533727   0.6855
dlnDCEsettle         10      .00917   0.1850   131.4072   0.0000
dlnspot              10     .004781   0.1432   96.73194   0.0000
----------------------------------------------------------------
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dlnspot      |
     dlnUSKS |
         L1. |   .1500384   .0165802     9.05   0.000     .1175417    .1825351
         L2. |   .0584598    .018415     3.17   0.002      .022367    .0945526
         L3. |   .0087386   .0186066     0.47   0.639    -.0277297    .0452069
             |
dlnDCEsettle |
         L1. |  -.0399387   .0223393    -1.79   0.074    -.0837229    .0038454
         L2. |  -.0175935   .0225214    -0.78   0.435    -.0617346    .0265476
         L3. |   -.005434   .0213128    -0.25   0.799    -.0472064    .0363384
             |
     dlnspot |
         L1. |   .0466202   .0429985     1.08   0.278    -.0376552    .1308957
         L2. |   .0114193   .0427308     0.27   0.789    -.0723316    .0951702
         L3. |   .0710896   .0414763     1.71   0.087    -.0102026    .1523817
             |
       _cons |   .0001704   .0001975     0.86   0.388    -.0002167    .0005575
------------------------------------------------------------------------------
      +------------------------------------------------------------------+
      |          Equation           Excluded |   chi2     df Prob > chi2 |
      |--------------------------------------+---------------------------|
      |           dlnUSKS       dlnDCEsettle |  5.4302     3    0.143    |
      |           dlnUSKS            dlnspot |  .28132     3    0.964    |
      |           dlnUSKS                ALL |  5.7578     6    0.451    |
      |--------------------------------------+---------------------------|
      |      dlnDCEsettle            dlnUSKS |  91.763     3    0.000    |
      |      dlnDCEsettle            dlnspot |  5.9407     3    0.115    |
      |      dlnDCEsettle                ALL |  98.324     6    0.000    |
      |--------------------------------------+---------------------------|
      |           dlnspot            dlnUSKS |  90.244     3    0.000    |
      |           dlnspot       dlnDCEsettle |  4.4328     3    0.218    |
      |           dlnspot                ALL |  90.824     6    0.000    |
      +------------------------------------------------------------------+
```

Table 16: estimation results for US spot, DCE settlement price, prewar

Similar with previous results, the US spot price had predicting power with respect to the Chinese spot price under 1% level. But the Chinese spot price is not predictive of the US spot price, according to another estimation.

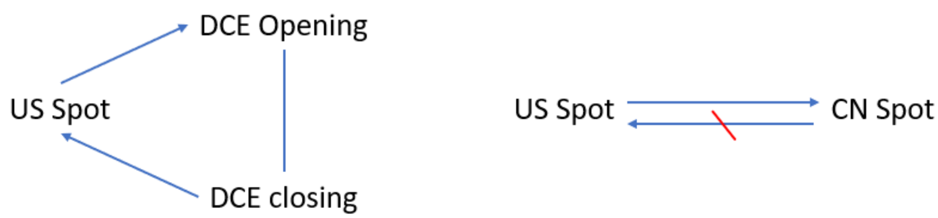


Figure 35: price relationships before trade war

To sum up, before declaration of the trade war, there was a circular relationship between DCE prices and the US spot price. The Chinese spot price could also be inferred from the US spot price, but not vice versa. These results are similar to previous estimations using US futures prices.

## 4.6 After the trade war, US spot, China futures and spot

### 4.6.1 US spot, DCE opening price

```
Sample:  600 - 756                              No. of obs      =       157
Log likelihood =  1590.068                      AIC             = -20.10278
FPE            =  3.73e-13                      HQIC            = -20.00791
Det(Sigma_ml)  =  3.20e-13                      SBIC            = -19.86918

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dlnUSKS               4     .013614   0.0050   .7839697   0.8533
dlnDCEopen            4      .01107   0.0014   .2251295   0.9734
dlnspot               4      .00391   0.0042    .662454   0.8820
----------------------------------------------------------------
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dlnDCEopen   |
     dlnUSKS |
         L1. |   .0257283   .0650558     0.40   0.692    -.1017788    .1532354
             |
  dlnDCEopen |
         L1. |  -.0057864   .0797891    -0.07   0.942    -.1621701    .1505973
             |
     dlnspot |
         L1. |  -.0599517   .2244726    -0.27   0.789    -.4999098    .3800065
             |
       _cons |  -.0005965   .0008813    -0.68   0.498    -.0023238    .0011308
```

```
-------------+----------------------------------------------------------------
      +------------------------------------------------------------------+
      |          Equation           Excluded |   chi2     df Prob > chi2 |
      |--------------------------------------+---------------------------|
      |           dlnUSKS         dlnDCEopen | .21663     1    0.642     |
      |           dlnUSKS            dlnspot | .35592     1    0.551     |
      |           dlnUSKS                ALL | .56543     2    0.754     |
      |--------------------------------------+---------------------------|
      |        dlnDCEopen            dlnUSKS |  .1564     1    0.692     |
      |        dlnDCEopen            dlnspot | .07133     1    0.789     |
      |        dlnDCEopen                ALL |  .2212     2    0.895     |
      |--------------------------------------+---------------------------|
      |           dlnspot            dlnUSKS | .28953     1    0.591     |
      |           dlnspot         dlnDCEopen | .00345     1    0.953     |
      |           dlnspot                ALL | .29117     2    0.865     |
      +------------------------------------------------------------------+
```

Table 17: estimation results for US spot, DCE opening price, after war

After the trade war, the US spot price no longer inferring DCE opening price anymore.

### 4.6.2 US spot, DCE closing price

```
Sample:  582 - 733                                 No. of obs      =       152
Log likelihood =  1530.235                         AIC             = -19.97678
FPE            =  4.23e-13                         HQIC            =  -19.8798
Det(Sigma_ml)  =  3.62e-13                         SBIC            = -19.73805

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
ldlnUSKS              4     .013803   0.0027   .4125522   0.9376
dlnDCEclose           4     .011642   0.0099   1.520228   0.6776
dlnspot               4     .003962   0.0184    2.85479   0.4146
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ldlnUSKS     |
    ldlnUSKS |
         L1. |  -.0383284   .0814861    -0.47   0.638    -.1980382    .1213814
             |
 dlnDCEclose |
         L1. |  -.0133471   .0972371    -0.14   0.891    -.2039284    .1772341
             |
     dlnspot |
         L1. |   .1223821   .2833479     0.43   0.666    -.4329697    .6777339
             |
       _cons |  -.0000385   .0011144    -0.03   0.972    -.0022227    .0021458
-------------+----------------------------------------------------------------
      +------------------------------------------------------------------+
      |          Equation           Excluded |   chi2     df Prob > chi2 |
      |--------------------------------------+---------------------------|
      |          ldlnUSKS        dlnDCEclose | .01884     1    0.891     |
      |          ldlnUSKS            dlnspot | .18655     1    0.666     |
      |          ldlnUSKS                ALL | .19186     2    0.909     |
      |--------------------------------------+---------------------------|
```

```
|       dlnDCEclose           ldlnUSKS |  .00677     1    0.934    |
|       dlnDCEclose            dlnspot |  1.0138     1    0.314    |
|       dlnDCEclose                ALL |  1.0169     2    0.601    |
|--------------------------------------+--------------------------|
|           dlnspot           ldlnUSKS |  1.4651     1    0.226    |
|           dlnspot        dlnDCEclose |  1.0715     1    0.301    |
|           dlnspot                ALL |  2.3075     2    0.315    |
+-----------------------------------------------------------------+
```

Table 18: estimation results for US spot, DCE closing price, after war

After the trade war, the US spot price no longer inferred the DCE opening price.

#### 4.6.3 US spot, Chinese spot price

```
Sample:  586 - 744                                 No. of obs      =       159
Log likelihood =  1643.746                         AIC             =  -20.5251
FPE            =  2.45e-13                         HQIC            = -20.43105
Det(Sigma_ml)  =  2.10e-13                         SBIC            = -20.29349

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dlnUSKS               4     .013501   0.0085   1.368087   0.7130
dlnDCEsettle          4     .009643   0.0467   7.791433   0.0505
dlnspot               4     .003713   0.0145    2.33598   0.5057
----------------------------------------------------------------
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dlnspot      |
     dlnUSKS |
         L1. |   .0114674   .0218027     0.53   0.599    -.0312651    .0541999
             |
dlnDCEsettle |
         L1. |  -.0407301   .0300994    -1.35   0.176    -.0997238    .0182636
             |
     dlnspot |
         L1. |   .0369941   .0790343     0.47   0.640    -.1179102    .1918984
             |
       _cons |  -.0004988    .000294    -1.70   0.090     -.001075    .0000775
------------------------------------------------------------------------------
      +-----------------------------------------------------------------+
      |          Equation           Excluded |   chi2     df Prob > chi2 |
      |--------------------------------------+--------------------------|
      |           dlnUSKS       dlnDCEsettle |  1.1038     1    0.293    |
      |           dlnUSKS            dlnspot |  .06677     1    0.796    |
      |           dlnUSKS                ALL |  1.1191     2    0.571    |
      |--------------------------------------+--------------------------|
      |      dlnDCEsettle            dlnUSKS |  4.8941     1    0.027    |
      |      dlnDCEsettle            dlnspot |  .05411     1    0.816    |
      |      dlnDCEsettle                ALL |  4.9069     2    0.086    |
      |--------------------------------------+--------------------------|
      |           dlnspot            dlnUSKS |  .27664     1    0.599    |
      |           dlnspot       dlnDCEsettle |  1.8311     1    0.176    |
      |           dlnspot                ALL |  2.2307     2    0.328    |
      +-----------------------------------------------------------------+
```

Table 19: estimation results for US spot, DCE settlement price, after war

After the trade war, the US spot price no longer inferring Chinese spot price anymore.

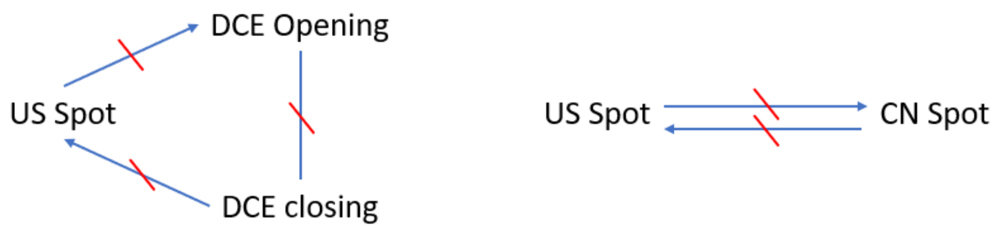


Figure 36: price relationships, after war

To sum up, when we replace US futures prices with the US spot price, market segmentation still exists after the trade war.

To make sure of robustness, we also switched spot prices for both Chinese spot prices and US spot prices during regressions. Unit conversion estimation was also conducted. All give similar results. Model steadiness and autocorrelation assumption were also checked and gave positive results.

# CHAPTER 5 CONCLUSION

In this paper, we first used the VAR model to estimate the circulated price signaling structure between China and US soybean futures prices, including two opening prices and two closing prices. We also discovered the relationships between US soybean futures prices and the Chinese spot price of soybeans. Price relationships before the trade war could be summarized as follows:

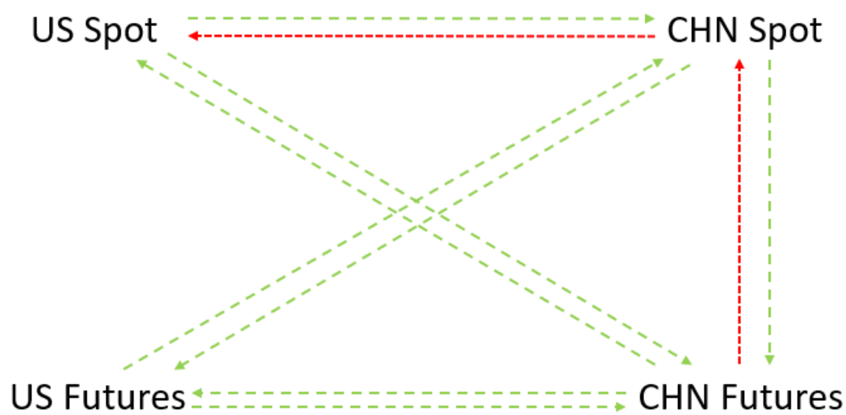


Figure 37: price relationships before trade war

Lines in green indicate there is signaling effect between two prices in certain directions, while red lines mean there are no relationships. Clearly, the US and Chinese markets had multiple relationships before the trade war. First, we detected circularity relationships between two futures markets using the opening and closing price of two markets. Next, we found there was signaling effect between the US futures settlement price and the Chinese spot price. Third, we found that the US spot price was also inferable from the Chinese spot price. Fourth, we found that the US spot price and Chinese futures price interacted with each other. These results are significant no matter what the currency exchange effects. However, the Chinese spot market of soybeans had little predictive power with respect to the US spot market, and the previously prevailing theory that futures price could guide spot price was not proven to be correct in the Chinese soybean market.

Once the trade war began, none of these relationships was significant anymore. We can conclude that the trade war made the two markets segmented in terms of soybean trading. This effect is proved in both the futures market and the spot market. Based on this result, it is reasonable to infer that a retaliatory trade war or retaliatory tariffs could adversely affect the efficiency of a market, introducing trade restrictions that sever the linkage between markets. It is reasonable to predict various negative effects, therefore. International traders would have to renegotiate their trade terms and conditions, while commodity derivatives traders would have to rebuild their hedging or speculation portfolios, as previously normative price patterns would no longer be operative. Both US producers and Chinese consumers would likely be in danger of suffering deteriorated market conditions.

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# APPENDIX

## Relative estimation results

```
pre war, CBOT close & DCE open & spot CNQD
. varsoc dlnCBOTclose dlnDCEopen dlnspot

   Selection-order criteria
   Sample:  6 - 597                            Number of obs      =       592
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  5867.76                      5.0e-13  -19.8134  -19.8047  -19.7912  |
  |  1 |  5927.55  119.58    9  0.000  4.2e-13   -19.985  -19.9504  -19.8961* |
  |  2 |   5951.5  47.889*   9  0.000  4.0e-13* -20.0355* -19.9749*    -19.88  |
  |  3 |  5956.53  10.071    9  0.345  4.0e-13  -20.0221  -19.9355  -19.7999  |
  |  4 |  5964.82  16.575    9  0.056  4.1e-13  -20.0197  -19.9072  -19.7309  |
  +---------------------------------------------------------------------------+
   Endogenous:  dlnCBOTclose dlnDCEopen dlnspot
    Exogenous:  _cons

. var dlnCBOTclose dlnDCEopen dlnspot, lag(1/2)

Vector autoregression

Sample:  4 - 597                                  No. of obs      =       594
Log likelihood =  5972.985                        AIC             = -20.04035
FPE            =  3.97e-13                        HQIC            = -19.97995
Det(Sigma_ml)  =  3.70e-13                        SBIC            = -19.88526

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dlnCBOTclose          7     .011772   0.0071   4.276981   0.6392
dlnDCEopen            7     .011283   0.1284   87.51036   0.0000
dlnspot               7     .004692   0.1513   105.8933   0.0000
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dlnCBOTclose |
dlnCBOTclose |
         L1. |  -.0122471   .0411161    -0.30   0.766    -.0928331    .0683389
         L2. |   .0767552   .0445261     1.72   0.085    -.0105142    .1640247
             |
  dlnDCEopen |
         L1. |  -.0027636   .0417768    -0.07   0.947    -.0846446    .0791175
         L2. |   .0289284   .0409047     0.71   0.479    -.0512434    .1091001
             |
     dlnspot |
```

```
         L1. |  -.132609   .1032077    -1.28   0.199    -.3348924    .0696744
         L2. |  .0071246   .0985869     0.07   0.942    -.1861022    .2003514
             |
       _cons |  .0001373    .000481     0.29   0.775    -.0008054      .00108


------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dlnDCEopen   |
dlnCBOTclose |
         L1. |  .1914491   .0394096     4.86   0.000     .1142078    .2686905
         L2. |  .2414322    .042678     5.66   0.000     .1577848    .3250796
             |
  dlnDCEopen |
         L1. | -.0806957   .0400429    -2.02   0.044    -.1591783   -.0022131
         L2. | -.0961642    .039207    -2.45   0.014    -.1730085   -.0193199
             |
     dlnspot |
         L1. |   .256136   .0989242     2.59   0.010     .0622482    .4500238
         L2. |  -.101227   .0944952    -1.07   0.284    -.2864341    .0839801
             |
       _cons | -.0001038    .000461    -0.23   0.822    -.0010074    .0007998
-------------+----------------------------------------------------------------
dlnspot      |
dlnCBOTclose |
         L1. |  .1592897   .0163882     9.72   0.000     .1271694    .1914099
         L2. |  .0452103   .0177474     2.55   0.011     .0104261    .0799945
             |
  dlnDCEopen |
         L1. | -.0308657   .0166516    -1.85   0.064    -.0635022    .0017707
         L2. | -.0193845    .016304    -1.19   0.234    -.0513397    .0125706
             |
     dlnspot |
         L1. |  .0359535   .0411369     0.87   0.382    -.0446734    .1165804
         L2. |  .0386101   .0392951     0.98   0.326     -.038407    .1156271
             |
       _cons |  .0001565   .0001917     0.82   0.414    -.0002193    .0005323
------------------------------------------------------------------------------

. vargranger

   Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |      dlnCBOTclose         dlnDCEopen |  .51098     2    0.775    |
  |      dlnCBOTclose            dlnspot |  1.6509     2    0.438    |
  |      dlnCBOTclose                ALL |  2.3381     4    0.674    |
  |--------------------------------------+---------------------------|
  |        dlnDCEopen       dlnCBOTclose |  54.499     2    0.000    |
  |        dlnDCEopen            dlnspot |  7.5665     2    0.023    |
  |        dlnDCEopen                ALL |  79.631     4    0.000    |
  |--------------------------------------+---------------------------|
  |           dlnspot       dlnCBOTclose |  99.991     2    0.000    |
  |           dlnspot         dlnDCEopen |  4.6275     2    0.099    |
  |           dlnspot                ALL |  102.93     4    0.000    |
  +------------------------------------------------------------------+

. varstable

   Eigenvalue stability condition
  +----------------------------------------+
```

```
  |        Eigenvalue        |   Modulus   |
  |--------------------------+-------------|
  | -.02960317 +  .3952616i  |   .396369   |
  | -.02960317 -  .3952616i  |   .396369   |
  |  -.3264485               |   .326448   |
  |   .2722697 + .04171633i  |   .275447   |
  |   .2722697 - .04171633i  |   .275447   |
  |  -.2158738               |   .215874   |
  +--------------------------------------+
   All the eigenvalues lie inside the unit circle.
   VAR satisfies stability condition.


. varlmar

   Lagrange-multiplier test
  +--------------------------------------+
  | lag  |      chi2    df   Prob > chi2 |
  |------+-------------------------------|
  |   1  |   11.1155     9     0.26788   |
  |   2  |   10.8025     9     0.28949   |
  +--------------------------------------+
   H0: no autocorrelation at lag order
```

pre war, CBOT close & DCE open & spot CNSH

```
. varsoc dlnCBOTclose dlnDCEopen dlnspot

   Selection-order criteria
   Sample:  6 - 597                            Number of obs      =       592
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  5875.53                       4.9e-13  -19.8396   -19.831  -19.8174  |
  |  1 |  5933.69  116.32    9  0.000  4.1e-13  -20.0057  -19.9711  -19.9169* |
  |  2 |  5958.11  48.826    9  0.000  3.9e-13* -20.0578* -19.9972* -19.9023  |
  |  3 |  5963.45  10.689    9  0.298  4.0e-13  -20.0454  -19.9589  -19.8233  |
  |  4 |  5972.22   17.54*   9  0.041  4.0e-13  -20.0447  -19.9322  -19.7559  |
  +---------------------------------------------------------------------------+
   Endogenous:  dlnCBOTclose dlnDCEopen dlnspot
    Exogenous:  _cons

. var dlnCBOTclose dlnDCEopen dlnspot, lag(1/2)

Vector autoregression

Sample:  4 - 597                                  No. of obs      =       594
Log likelihood =  5979.617                        AIC             = -20.06268
FPE            =  3.89e-13                        HQIC            = -20.00228
Det(Sigma_ml)  =  3.62e-13                        SBIC            = -19.90759

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dlnCBOTclose          7     .011773   0.0069    4.12177   0.6602
dlnDCEopen            7     .011267   0.1309   89.46131   0.0000
dlnspot               7     .004644   0.1457   101.3403   0.0000
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dlnCBOTclose |
dlnCBOTclose |
```

```
         L1. |  -.0139039   .0411091    -0.34   0.735    -.0944762    .0666685
         L2. |   .0702982   .0444134     1.58   0.113    -.0167505    .1573468
             |
  dlnDCEopen |
         L1. |   .0014255   .0418405     0.03   0.973    -.0805803    .0834314
         L2. |    .035801   .0408702     0.88   0.381    -.0443032    .1159053
             |
     dlnspot |
         L1. |  -.1038018   .1041745    -1.00   0.319      -.30798    .1003764
         L2. |  -.0654685   .1002887    -0.65   0.514    -.2620307    .1310937
             |
       _cons |   .0001436    .000481     0.30   0.765    -.0007991    .0010862
-------------+----------------------------------------------------------------
dlnDCEopen   |
dlnCBOTclose |
         L1. |   .1940892   .0393415     4.93   0.000     .1169812    .2711972
         L2. |   .2374982   .0425037     5.59   0.000     .1541924     .320804
             |
  dlnDCEopen |
         L1. |   -.081485   .0400415    -2.04   0.042    -.1599648   -.0030052
         L2. |  -.0964984   .0391129    -2.47   0.014    -.1731583   -.0198385
             |
     dlnspot |
         L1. |   .2882491   .0996952     2.89   0.004     .0928501    .4836482
         L2. |   -.107866   .0959765    -1.12   0.261    -.2959766    .0802445
             |
       _cons |  -.0001038   .0004603    -0.23   0.822     -.001006    .0007983
-------------+----------------------------------------------------------------
dlnspot      |
dlnCBOTclose |
         L1. |   .1531601    .016215     9.45   0.000     .1213793    .1849409
         L2. |   .0431545   .0175183     2.46   0.014     .0088192    .0774898
             |
  dlnDCEopen |
         L1. |  -.0271031   .0165035    -1.64   0.101    -.0594494    .0052431
         L2. |  -.0284437   .0161208    -1.76   0.078    -.0600399    .0031525
             |
     dlnspot |
         L1. |   .0410597   .0410904     1.00   0.318     -.039476    .1215954
         L2. |   .0374674   .0395577     0.95   0.344    -.0400642    .1149991
             |
       _cons |   .0001359   .0001897     0.72   0.474    -.0002359    .0005077
------------------------------------------------------------------------------

. vargranger

   Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |      dlnCBOTclose         dlnDCEopen |  .76754     2    0.681    |
  |      dlnCBOTclose            dlnspot |  1.4964     2    0.473    |
  |      dlnCBOTclose                ALL |  2.1834     4    0.702    |
  |--------------------------------------+---------------------------|
  |        dlnDCEopen       dlnCBOTclose |  54.826     2    0.000    |
  |        dlnDCEopen            dlnspot |  9.2886     2    0.010    |
  |        dlnDCEopen                ALL |   81.56     4    0.000    |
  |--------------------------------------+---------------------------|
  |           dlnspot       dlnCBOTclose |  94.675     2    0.000    |
  |           dlnspot         dlnDCEopen |  5.5037     2    0.064    |
  |           dlnspot                ALL |   98.59     4    0.000    |
  +------------------------------------------------------------------+
```

```
.
. varstable, graph

   Eigenvalue stability condition
  +--------------------------------------+
  |        Eigenvalue        |   Modulus  |
  |--------------------------+-------------|
  | -.01554094 +  .3915894i  |   .391898   |
  | -.01554094 -  .3915894i  |   .391898   |
  |  -.3571575               |   .357157   |
  |   .2626243 + .07657747i  |   .273561   |
  |   .2626243 - .07657747i  |   .273561   |
  |  -.1913384               |   .191338   |
  +--------------------------------------+
   All the eigenvalues lie inside the unit circle.
   VAR satisfies stability condition.

.
. varlmar

   Lagrange-multiplier test
  +------------------------------------+
  | lag  |      chi2    df   Prob > chi2 |
  |------+-----------------------------|
  |   1  |   11.2043     9     0.26197   |
  |   2  |   14.5620     9     0.10369   |
  +------------------------------------+
   H0: no autocorrelation at lag order
```

pre war, CBOT close & DCE open & spot CNNT

```
. varsoc dlnCBOTclose dlnDCEopen dlnspot

   Selection-order criteria
   Sample:  6 - 597                           Number of obs      =       592
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  5895.53                      4.5e-13  -19.9072  -19.8985   -19.885  |
  |  1 |  5946.58  102.11    9  0.000  3.9e-13  -20.0493  -20.0147  -19.9604* |
  |  2 |  5972.36  51.555*   9  0.000  3.7e-13* -20.1059* -20.0454* -19.9505  |
  |  3 |   5978.6  12.486    9  0.187  3.8e-13  -20.0966  -20.0101  -19.8745  |
  |  4 |     5986  14.803    9  0.096  3.8e-13  -20.0912  -19.9787  -19.8025  |
  +---------------------------------------------------------------------------+
   Endogenous:  dlnCBOTclose dlnDCEopen dlnspot
    Exogenous:  _cons

. var dlnCBOTclose dlnDCEopen dlnspot, lag(1/2)

Vector autoregression

Sample:  4 - 597                                 No. of obs      =       594
Log likelihood =  5993.891                       AIC             = -20.11074
FPE            =  3.70e-13                       HQIC            = -20.05034
Det(Sigma_ml)  =  3.45e-13                       SBIC            = -19.95565

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dlnCBOTclose          7     .011781   0.0056   3.329566   0.7665
dlnDCEopen            7     .011301   0.1257   85.37078   0.0000
dlnspot               7     .004519   0.1366    93.9769   0.0000
```

```
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dlnCBOTclose |
dlnCBOTclose |
         L1. |   -.013409   .0411297    -0.33   0.744    -.0940218    .0672038
         L2. |   .0646199   .0441279     1.46   0.143    -.0218692     .151109
             |
  dlnDCEopen |
         L1. |  -.0021736   .0417084    -0.05   0.958    -.0839205    .0795733
         L2. |   .0354345   .0409311     0.87   0.387     -.044789    .1156581
             |
     dlnspot |
         L1. |  -.0670454   .1071116    -0.63   0.531    -.2769803    .1428895
         L2. |  -.0535645   .1030449    -0.52   0.603    -.2555287    .1483997
             |
       _cons |   .0001376   .0004815     0.29   0.775    -.0008061    .0010812
-------------+----------------------------------------------------------------
dlnDCEopen   |
dlnCBOTclose |
         L1. |   .1948105   .0394534     4.94   0.000     .1174832    .2721378
         L2. |    .248626   .0423294     5.87   0.000     .1656618    .3315901
             |
  dlnDCEopen |
         L1. |  -.0830293   .0400085    -2.08   0.038    -.1614445   -.0046141
         L2. |  -.1008268   .0392629    -2.57   0.010    -.1777807   -.0238729
             |
     dlnspot |
         L1. |   .2374864   .1027461     2.31   0.021     .0361077    .4388651
         L2. |  -.0720762   .0988451    -0.73   0.466    -.2658091    .1216566
             |
       _cons |  -.0001074   .0004618    -0.23   0.816    -.0010126    .0007977
-------------+----------------------------------------------------------------
dlnspot      |
dlnCBOTclose |
         L1. |   .1406774   .0157778     8.92   0.000     .1097534    .1716015
         L2. |   .0479733    .016928     2.83   0.005     .0147951    .0811516
             |
  dlnDCEopen |
         L1. |  -.0240479   .0159998    -1.50   0.133     -.055407    .0073112
         L2. |  -.0280541   .0157017    -1.79   0.074    -.0588288    .0027205
             |
     dlnspot |
         L1. |   .0450863   .0410893     1.10   0.273    -.0354472    .1256198
         L2. |   .0299991   .0395292     0.76   0.448    -.0474768     .107475
             |
       _cons |   .0001591   .0001847     0.86   0.389    -.0002029     .000521
------------------------------------------------------------------------------

. vargranger

   Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |      dlnCBOTclose         dlnDCEopen |  .75886     2    0.684    |
  |      dlnCBOTclose            dlnspot |  .70765     2    0.702    |
  |      dlnCBOTclose                ALL |  1.3938     4    0.845    |
  |--------------------------------------+---------------------------|
  |        dlnDCEopen       dlnCBOTclose |  58.191     2    0.000    |
  |        dlnDCEopen            dlnspot |  5.6779     2    0.058    |
```

```
  |        dlnDCEopen                ALL |  77.516     4    0.000    |
  |------------------------------------+--------------------------|
  |           dlnspot       dlnCBOTclose |  86.933     2    0.000    |
  |           dlnspot         dlnDCEopen |  5.1878     2    0.075    |
  |           dlnspot                ALL |  90.653     4    0.000    |
  +---------------------------------------------------------------+

.
. varstable, graph

   Eigenvalue stability condition
  +----------------------------------------+
  |        Eigenvalue        |   Modulus   |
  |--------------------------+-------------|
  | -.01908702 +  .3887615i  |    .38923   |
  | -.01908702 -  .3887615i  |    .38923   |
  |   -.342351               |   .342351   |
  |   .2513632 +  .0574073i  |   .257835   |
  |   .2513632 -  .0574073i  |   .257835   |
  |  -.1735534               |   .173553   |
  +----------------------------------------+
   All the eigenvalues lie inside the unit circle.
   VAR satisfies stability condition.

.
. varlmar

   Lagrange-multiplier test
  +--------------------------------------+
  | lag  |      chi2    df   Prob > chi2 |
  |------+-------------------------------|
  |   1  |   14.4432     9     0.10741   |
  |   2  |   11.2023     9     0.26209   |
  +--------------------------------------+
   H0: no autocorrelation at lag order



after war, CBOT close & DCE open & spot CNQD
still do model validation to ensure the model is set properly
. varsoc dlnCBOTclose dlnDCEopen dlnspot

   Selection-order criteria
   Sample:  603 - 756                          Number of obs      =       154
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  1576.85                      2.7e-13* -20.4396* -20.4156* -20.3805* |
  |  1 |  1578.32  2.9288    9  0.967  2.9e-13  -20.3418  -20.2456  -20.1051  |
  |  2 |  1585.92  15.212    9  0.085  3.0e-13  -20.3237  -20.1554  -19.9095  |
  |  3 |  1592.57  13.294    9  0.150  3.1e-13  -20.2931  -20.0528  -19.7015  |
  |  4 |  1597.22   9.312    9  0.409  3.3e-13  -20.2367  -19.9243  -19.4676  |
  +---------------------------------------------------------------------------+
   Endogenous:  dlnCBOTclose dlnDCEopen dlnspot
    Exogenous:  _cons

. var dlnCBOTclose dlnDCEopen dlnspot, lag(1)

Vector autoregression

Sample:  600 - 756                                  No. of obs      =       157
Log likelihood =  1607.491                          AIC             = -20.32473
FPE            =  2.99e-13                          HQIC            = -20.22986
```

```
Det(Sigma_ml)  =  2.57e-13                         SBIC            = -20.09113

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dlnCBOTclose          4     .012161   0.0137   2.173677   0.5372
dlnDCEopen            4     .011075   0.0004   .0690777   0.9953
dlnspot               4      .00391   0.0042   .6544733   0.8839
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dlnCBOTclose |
dlnCBOTclose |
         L1. |  -.0889994   .0795503    -1.12   0.263    -.2449152    .0669163
             |
  dlnDCEopen |
         L1. |  -.0576678   .0876086    -0.66   0.510    -.2293775    .1140419
             |
     dlnspot |
         L1. |   .1745235   .2464874     0.71   0.479    -.3085829    .6576299
             |
       _cons |   .0000173   .0009682     0.02   0.986    -.0018804     .001915
-------------+----------------------------------------------------------------
dlnDCEopen   |
dlnCBOTclose |
         L1. |   .0014865   .0724443     0.02   0.984    -.1405017    .1434748
             |
  dlnDCEopen |
         L1. |  -.0047171   .0797827    -0.06   0.953    -.1610884    .1516542
             |
     dlnspot |
         L1. |  -.0571176   .2244693    -0.25   0.799    -.4970693    .3828341
             |
       _cons |  -.0005965   .0008817    -0.68   0.499    -.0023247    .0011317
-------------+----------------------------------------------------------------
dlnspot      |
dlnCBOTclose |
         L1. |   .0135709   .0255753     0.53   0.596    -.0365558    .0636976
             |
  dlnDCEopen |
         L1. |  -.0011745   .0281661    -0.04   0.967     -.056379    .0540299
             |
     dlnspot |
         L1. |  -.0483147   .0792454    -0.61   0.542    -.2036328    .1070034
             |
       _cons |  -.0005267   .0003113    -1.69   0.091    -.0011368    .0000834
------------------------------------------------------------------------------

.
. vargranger

   Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |      dlnCBOTclose         dlnDCEopen |  .43329     1    0.510    |
  |      dlnCBOTclose            dlnspot |  .50132     1    0.479    |
  |      dlnCBOTclose                ALL |  .92164     2    0.631    |
  |--------------------------------------+---------------------------|
  |        dlnDCEopen       dlnCBOTclose |  .00042     1    0.984    |
  |        dlnDCEopen            dlnspot |  .06475     1    0.799    |
  |        dlnDCEopen                ALL |  .06515     2    0.968    |
```

```
  |------------------------------------+---------------------------|
  |          dlnspot       dlnCBOTclose |  .28156     1    0.596    |
  |          dlnspot         dlnDCEopen |  .00174     1    0.967    |
  |          dlnspot                ALL |   .2832     2    0.868    |
  +----------------------------------------------------------------+

.
. varstable

   Eigenvalue stability condition
  +----------------------------------------+
  |        Eigenvalue        |   Modulus   |
  |--------------------------+-------------|
  |  -.1171515               |   .117151   |
  | -.03415502               |   .034155   |
  |  .00927528               |   .009275   |
  +----------------------------------------+
   All the eigenvalues lie inside the unit circle.
   VAR satisfies stability condition.

.
. varlmar

   Lagrange-multiplier test
  +--------------------------------------+
  | lag  |      chi2    df   Prob > chi2 |
  |------+-------------------------------|
  |   1  |   14.6388     9     0.10135   |
  |   2  |   12.3426     9     0.19468   |
  +--------------------------------------+
   H0: no autocorrelation at lag order


after war, CBOT close & DCE open & spot CNSH
still do model validation to ensure the model is set properly

. varsoc dlnCBOTclose dlnDCEopen dlnspot

   Selection-order criteria
   Sample:  603 - 756                          Number of obs      =       154
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  1576.85                      2.7e-13* -20.4396* -20.4156* -20.3805* |
  |  1 |  1578.32  2.9288    9  0.967  2.9e-13  -20.3418  -20.2456  -20.1051  |
  |  2 |  1585.92  15.212    9  0.085  3.0e-13  -20.3237  -20.1554  -19.9095  |
  |  3 |  1592.57  13.294    9  0.150  3.1e-13  -20.2931  -20.0528  -19.7015  |
  |  4 |  1597.22   9.312    9  0.409  3.3e-13  -20.2367  -19.9243  -19.4676  |
  +---------------------------------------------------------------------------+
   Endogenous:  dlnCBOTclose dlnDCEopen dlnspot
    Exogenous:  _cons

.
. var dlnCBOTclose dlnDCEopen dlnspot, lag(1)

Vector autoregression

Sample:  600 - 756                                No. of obs      =       157
Log likelihood =  1607.491                        AIC             = -20.32473
FPE            =  2.99e-13                        HQIC            = -20.22986
Det(Sigma_ml)  =  2.57e-13                        SBIC            = -20.09113

Equation           Parms      RMSE     R-sq      chi2     P>chi2
```

```
----------------------------------------------------------------
dlnCBOTclose          4     .012161   0.0137   2.173677   0.5372
dlnDCEopen            4     .011075   0.0004   .0690777   0.9953
dlnspot               4      .00391   0.0042   .6544733   0.8839
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dlnCBOTclose |
dlnCBOTclose |
         L1. |  -.0889994   .0795503    -1.12   0.263    -.2449152    .0669163
             |
  dlnDCEopen |
         L1. |  -.0576678   .0876086    -0.66   0.510    -.2293775    .1140419
             |
     dlnspot |
         L1. |   .1745235   .2464874     0.71   0.479    -.3085829    .6576299
             |
       _cons |   .0000173   .0009682     0.02   0.986    -.0018804     .001915
-------------+----------------------------------------------------------------
dlnDCEopen   |
dlnCBOTclose |
         L1. |   .0014865   .0724443     0.02   0.984    -.1405017    .1434748
             |
  dlnDCEopen |
         L1. |  -.0047171   .0797827    -0.06   0.953    -.1610884    .1516542
             |
     dlnspot |
         L1. |  -.0571176   .2244693    -0.25   0.799    -.4970693    .3828341
             |
       _cons |  -.0005965   .0008817    -0.68   0.499    -.0023247    .0011317
-------------+----------------------------------------------------------------
dlnspot      |
dlnCBOTclose |
         L1. |   .0135709   .0255753     0.53   0.596    -.0365558    .0636976
             |
  dlnDCEopen |
         L1. |  -.0011745   .0281661    -0.04   0.967     -.056379    .0540299
             |
     dlnspot |
         L1. |  -.0483147   .0792454    -0.61   0.542    -.2036328    .1070034
             |
       _cons |  -.0005267   .0003113    -1.69   0.091    -.0011368    .0000834
------------------------------------------------------------------------------

.
. vargranger

   Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |      dlnCBOTclose         dlnDCEopen |  .43329     1    0.510    |
  |      dlnCBOTclose            dlnspot |  .50132     1    0.479    |
  |      dlnCBOTclose                ALL |  .92164     2    0.631    |
  |--------------------------------------+---------------------------|
  |        dlnDCEopen       dlnCBOTclose |  .00042     1    0.984    |
  |        dlnDCEopen            dlnspot |  .06475     1    0.799    |
  |        dlnDCEopen                ALL |  .06515     2    0.968    |
  |--------------------------------------+---------------------------|
  |           dlnspot       dlnCBOTclose |  .28156     1    0.596    |
  |           dlnspot         dlnDCEopen |  .00174     1    0.967    |
```

```
  |          dlnspot              ALL |   .2832     2    0.868    |
  +-----------------------------------------------------------------+

.
. varstable

   Eigenvalue stability condition
  +----------------------------------------+
  |        Eigenvalue        |   Modulus   |
  |--------------------------+-------------|
  |  -.1171515               |   .117151   |
  | -.03415502               |   .034155   |
  |  .00927528               |   .009275   |
  +----------------------------------------+
   All the eigenvalues lie inside the unit circle.
   VAR satisfies stability condition.

.
. varlmar

   Lagrange-multiplier test
  +--------------------------------------+
  | lag  |      chi2    df   Prob > chi2 |
  |------+-------------------------------|
  |   1  |   14.6388     9     0.10135   |
  |   2  |   12.3426     9     0.19468   |
  +--------------------------------------+
   H0: no autocorrelation at lag order
```

after war, CBOT close & DCE open & spot CNNT
still do model validation to ensure the model is set properly

```
. varsoc dlnCBOTclose dlnDCEopen dlnspot

   Selection-order criteria
   Sample:  603 - 756                          Number of obs      =       154
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  1576.85                      2.7e-13* -20.4396* -20.4156* -20.3805* |
  |  1 |  1578.32  2.9288    9  0.967  2.9e-13  -20.3418  -20.2456  -20.1051  |
  |  2 |  1585.92  15.212    9  0.085  3.0e-13  -20.3237  -20.1554  -19.9095  |
  |  3 |  1592.57  13.294    9  0.150  3.1e-13  -20.2931  -20.0528  -19.7015  |
  |  4 |  1597.22   9.312    9  0.409  3.3e-13  -20.2367  -19.9243  -19.4676  |
  +---------------------------------------------------------------------------+
   Endogenous:  dlnCBOTclose dlnDCEopen dlnspot
    Exogenous:  _cons

.
. var dlnCBOTclose dlnDCEopen dlnspot, lag(1)

Vector autoregression

Sample:  600 - 756                               No. of obs      =       157
Log likelihood =  1607.491                       AIC             = -20.32473
FPE            =  2.99e-13                       HQIC            = -20.22986
Det(Sigma_ml)  =  2.57e-13                       SBIC            = -20.09113

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
```

```
dlnCBOTclose          4     .012161   0.0137   2.173677   0.5372
dlnDCEopen            4     .011075   0.0004   .0690777   0.9953
dlnspot               4      .00391   0.0042   .6544733   0.8839
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dlnCBOTclose |
dlnCBOTclose |
         L1. |  -.0889994   .0795503    -1.12   0.263    -.2449152    .0669163
             |
  dlnDCEopen |
         L1. |  -.0576678   .0876086    -0.66   0.510    -.2293775    .1140419
             |
     dlnspot |
         L1. |   .1745235   .2464874     0.71   0.479    -.3085829    .6576299
             |
       _cons |   .0000173   .0009682     0.02   0.986    -.0018804     .001915
-------------+----------------------------------------------------------------
dlnDCEopen   |
dlnCBOTclose |
         L1. |   .0014865   .0724443     0.02   0.984    -.1405017    .1434748
             |
  dlnDCEopen |
         L1. |  -.0047171   .0797827    -0.06   0.953    -.1610884    .1516542
             |
     dlnspot |
         L1. |  -.0571176   .2244693    -0.25   0.799    -.4970693    .3828341
             |
       _cons |  -.0005965   .0008817    -0.68   0.499    -.0023247    .0011317
-------------+----------------------------------------------------------------
dlnspot      |
dlnCBOTclose |
         L1. |   .0135709   .0255753     0.53   0.596    -.0365558    .0636976
             |
  dlnDCEopen |
         L1. |  -.0011745   .0281661    -0.04   0.967     -.056379    .0540299
             |
     dlnspot |
         L1. |  -.0483147   .0792454    -0.61   0.542    -.2036328    .1070034
             |
       _cons |  -.0005267   .0003113    -1.69   0.091    -.0011368    .0000834
------------------------------------------------------------------------------

.
. vargranger

   Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |      dlnCBOTclose         dlnDCEopen |  .43329     1    0.510    |
  |      dlnCBOTclose            dlnspot |  .50132     1    0.479    |
  |      dlnCBOTclose                ALL |  .92164     2    0.631    |
  |--------------------------------------+---------------------------|
  |        dlnDCEopen       dlnCBOTclose |  .00042     1    0.984    |
  |        dlnDCEopen            dlnspot |  .06475     1    0.799    |
  |        dlnDCEopen                ALL |  .06515     2    0.968    |
  |--------------------------------------+---------------------------|
  |           dlnspot       dlnCBOTclose |  .28156     1    0.596    |
  |           dlnspot         dlnDCEopen |  .00174     1    0.967    |
  |           dlnspot                ALL |   .2832     2    0.868    |
```

```
  +------------------------------------------------------------------+

.
. varstable

   Eigenvalue stability condition
  +----------------------------------------+
  |        Eigenvalue        |   Modulus   |
  |--------------------------+-------------|
  |  -.1171515               |   .117151   |
  | -.03415502               |   .034155   |
  |  .00927528               |   .009275   |
  +----------------------------------------+
   All the eigenvalues lie inside the unit circle.
   VAR satisfies stability condition.

.
. varlmar

   Lagrange-multiplier test
  +--------------------------------------+
  | lag  |      chi2    df   Prob > chi2 |
  |------+-------------------------------|
  |   1  |   14.6388     9     0.10135   |
  |   2  |   12.3426     9     0.19468   |
  +--------------------------------------+
   H0: no autocorrelation at lag order

pre DCEclose, CBOTopen, spot CNQD

. varsoc ldlnCBOTopen dlnDCEclose dlnspot

   Selection-order criteria
   Sample:  7 - 578                            Number of obs      =       572
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  5688.67                      4.7e-13    -19.88  -19.8711  -19.8572  |
  |  1 |  5756.35  135.36    9  0.000  3.8e-13  -20.0851  -20.0495* -19.9939* |
  |  2 |  5767.05  21.412*   9  0.011  3.8e-13* -20.0911* -20.0288  -19.9314  |
  |  3 |  5771.46  8.8039    9  0.456  3.8e-13   -20.075   -19.986  -19.8469  |
  |  4 |  5776.55  10.189    9  0.335  3.9e-13  -20.0614  -19.9457  -19.7648  |
  +---------------------------------------------------------------------------+
   Endogenous:  ldlnCBOTopen dlnDCEclose dlnspot
    Exogenous:  _cons

. var ldlnCBOTopen dlnDCEclose dlnspot, lag(1/2)

Vector autoregression

Sample:  5 - 578                                  No. of obs      =       574
Log likelihood =  5788.852                        AIC             = -20.09704
FPE            =  3.75e-13                        HQIC            = -20.03493
Det(Sigma_ml)  =  3.49e-13                        SBIC            =  -19.9378

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
ldlnCBOTopen          7      .01069   0.2226   164.3134   0.0000
dlnDCEclose           7      .01137   0.0161   9.421452   0.1512
dlnspot               7     .005185   0.0077   4.469328   0.6134
----------------------------------------------------------------

------------------------------------------------------------------------------
```

```
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ldlnCBOTopen |
ldlnCBOTopen |
         L1. |  -.1123643   .0414982    -2.71   0.007    -.1936993   -.0310292
         L2. |   .0362641   .0372974     0.97   0.331    -.0368375    .1093657
             |
 dlnDCEclose |
         L1. |   .2715981   .0407653     6.66   0.000     .1916995    .3514967
         L2. |    .153957    .042338     3.64   0.000     .0709762    .2369379
             |
     dlnspot |
         L1. |   .6803404   .0901476     7.55   0.000     .5036544    .8570264
         L2. |  -.0643355   .0945117    -0.68   0.496     -.249575     .120904
             |
       _cons |    .000061   .0004443     0.14   0.891    -.0008098    .0009319
-------------+----------------------------------------------------------------
dlnDCEclose  |
ldlnCBOTopen |
         L1. |   .0259418   .0441386     0.59   0.557    -.0605683    .1124518
         L2. |   .0015872   .0396705     0.04   0.968    -.0761656      .07934
             |
 dlnDCEclose |
         L1. |    .051892   .0433591     1.20   0.231    -.0330903    .1368742
         L2. |  -.1195055   .0450318    -2.65   0.008    -.2077661   -.0312449
             |
     dlnspot |
         L1. |   -.081006   .0958833    -0.84   0.398    -.2689339    .1069218
         L2. |  -.0186397   .1005251    -0.19   0.853    -.2156653    .1783858
             |
       _cons |     .00005   .0004726     0.11   0.916    -.0008762    .0009763
-------------+----------------------------------------------------------------
dlnspot      |
ldlnCBOTopen |
         L1. |   .0166442   .0201273     0.83   0.408    -.0228046    .0560929
         L2. |   .0053133   .0180898     0.29   0.769    -.0301421    .0407688
             |
 dlnDCEclose |
         L1. |   .0261157   .0197718     1.32   0.187    -.0126363    .0648678
         L2. |  -.0080109   .0205346    -0.39   0.696    -.0482579    .0322362
             |
     dlnspot |
         L1. |   .0409592    .043723     0.94   0.349    -.0447363    .1266547
         L2. |  -.0048663   .0458397    -0.11   0.915    -.0947104    .0849778
             |
       _cons |   .0002118   .0002155     0.98   0.326    -.0002106    .0006341
------------------------------------------------------------------------------

.
. vargranger

   Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |      ldlnCBOTopen        dlnDCEclose |  59.787     2    0.000     |
  |      ldlnCBOTopen            dlnspot |   57.17     2    0.000     |
  |      ldlnCBOTopen                ALL |  161.19     4    0.000     |
  |--------------------------------------+---------------------------|
  |       dlnDCEclose       ldlnCBOTopen |  .34548     2    0.841     |
  |       dlnDCEclose            dlnspot |  .75788     2    0.685     |
  |       dlnDCEclose                ALL |   .9972     4    0.910     |
  |--------------------------------------+---------------------------|
```

```
  |           dlnspot       ldlnCBOTopen |  .73599     2    0.692    |
  |           dlnspot        dlnDCEclose |  1.8563     2    0.395    |
  |           dlnspot                ALL |  2.3914     4    0.664    |
  +------------------------------------------------------------------+

.
. varstable

   Eigenvalue stability condition
  +----------------------------------------+
  |        Eigenvalue        |   Modulus   |
  |--------------------------+-------------|
  |  .01116012 +   .336746i  |   .336931   |
  |  .01116012 -   .336746i  |   .336931   |
  |  -.2338362               |   .233836   |
  |   .1629275               |   .162928   |
  |   .1098999               |     .1099   |
  | -.08082454               |   .080825   |
  +----------------------------------------+
   All the eigenvalues lie inside the unit circle.
   VAR satisfies stability condition.

.
. varlmar

   Lagrange-multiplier test
  +--------------------------------------+
  | lag  |      chi2    df   Prob > chi2 |
  |------+-------------------------------|
  |   1  |    8.4263     9     0.49182   |
  |   2  |    6.4492     9     0.69426   |
  +--------------------------------------+
   H0: no autocorrelation at lag order
```

pre DCEclose, CBOTopen, spot CNSH

```
. varsoc ldlnCBOTopen dlnDCEclose dlnspot

   Selection-order criteria
   Sample:  7 - 578                             Number of obs      =       572
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  5699.51                     4.5e-13  -19.9179   -19.909  -19.8951  |
  |  1 |  5762.51     126    9  0.000  3.7e-13  -20.1067  -20.0711* -20.0154* |
  |  2 |   5774.4  23.777*   9  0.005  3.7e-13* -20.1168* -20.0545  -19.9571  |
  |  3 |   5778.9  8.9979    9  0.437  3.7e-13   -20.101  -20.0121  -19.8729  |
  |  4 |  5785.02  12.247    9  0.200  3.8e-13   -20.091  -19.9753  -19.7945  |
  +---------------------------------------------------------------------------+
   Endogenous:  ldlnCBOTopen dlnDCEclose dlnspot
    Exogenous:  _cons

. var ldlnCBOTopen dlnDCEclose dlnspot, lag(1/2)

Vector autoregression

Sample:  5 - 578                                   No. of obs      =       574
Log likelihood =  5796.247                         AIC             = -20.12281
FPE            =  3.66e-13                         HQIC            =  -20.0607
Det(Sigma_ml)  =  3.40e-13                         SBIC            = -19.96357
```

```
Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
ldlnCBOTopen          7     .010758   0.2126   155.0194   0.0000
dlnDCEclose           7     .011367   0.0167   9.772337   0.1346
dlnspot               7     .005124   0.0065   3.764696   0.7085
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ldlnCBOTopen |
ldlnCBOTopen |
         L1. |  -.1099963    .041484    -2.65   0.008    -.1913035   -.0286892
         L2. |   .0384043   .0375802     1.02   0.307    -.0352516    .1120602
             |
 dlnDCEclose |
         L1. |   .2718957   .0412719     6.59   0.000     .1910042    .3527872
         L2. |    .166676   .0428205     3.89   0.000     .0827494    .2506026
             |
     dlnspot |
         L1. |   .6419605   .0924463     6.94   0.000     .4607691    .8231519
         L2. |  -.1155297    .096143    -1.20   0.230    -.3039666    .0729072
             |
       _cons |   .0000921    .000447     0.21   0.837     -.000784    .0009681
-------------+----------------------------------------------------------------
dlnDCEclose  |
ldlnCBOTopen |
         L1. |   .0307227   .0438317     0.70   0.483    -.0551858    .1166312
         L2. |   .0036454    .039707     0.09   0.927    -.0741789    .0814697
             |
 dlnDCEclose |
         L1. |   .0528055   .0436076     1.21   0.226    -.0326638    .1382749
         L2. |  -.1167993   .0452438    -2.58   0.010    -.2054755   -.0281231
             |
     dlnspot |
         L1. |  -.0869002   .0976781    -0.89   0.374    -.2783457    .1045453
         L2. |  -.0541158    .101584    -0.53   0.594    -.2532168    .1449853
             |
       _cons |   .0000543   .0004723     0.11   0.909    -.0008714    .0009799
-------------+----------------------------------------------------------------
dlnspot      |
ldlnCBOTopen |
         L1. |   .0192114   .0197569     0.97   0.331    -.0195115    .0579342
         L2. |    .001727   .0178977     0.10   0.923    -.0333519    .0368059
             |
 dlnDCEclose |
         L1. |   .0180207   .0196559     0.92   0.359    -.0205042    .0565455
         L2. |  -.0128287   .0203934    -0.63   0.529     -.052799    .0271417
             |
     dlnspot |
         L1. |   .0429346   .0440279     0.98   0.329    -.0433584    .1292276
         L2. |   -.003437   .0457885    -0.08   0.940    -.0931807    .0863067
             |
       _cons |   .0001889   .0002129     0.89   0.375    -.0002283    .0006062
------------------------------------------------------------------------------

.
. vargranger

   Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
```

```
  |----------------------------------+---------------------------|
  |      ldlnCBOTopen       dlnDCEclose |  61.244     2    0.000    |
  |      ldlnCBOTopen            dlnspot |  49.225     2    0.000    |
  |      ldlnCBOTopen                ALL |  151.94     4    0.000    |
  |----------------------------------+---------------------------|
  |       dlnDCEclose      ldlnCBOTopen |  .49255     2    0.782    |
  |       dlnDCEclose            dlnspot |  1.1036     2    0.576    |
  |       dlnDCEclose                ALL |   1.343     4    0.854    |
  |----------------------------------+---------------------------|
  |           dlnspot      ldlnCBOTopen |  .94587     2    0.623    |
  |           dlnspot       dlnDCEclose |   1.182     2    0.554    |
  |           dlnspot                ALL |   1.818     4    0.769    |
  +--------------------------------------------------------------+

.
. varstable, graph

   Eigenvalue stability condition
  +----------------------------------------+
  |        Eigenvalue        |   Modulus   |
  |--------------------------+-------------|
  |  .00558583 +   .337662i  |   .337708   |
  |  .00558583 -   .337662i  |   .337708   |
  |   -.279023               |   .279023   |
  |   .1518944 +  .0601687i  |   .163377   |
  |   .1518944 -  .0601687i  |   .163377   |
  | -.05019353               |   .050194   |
  +----------------------------------------+
   All the eigenvalues lie inside the unit circle.
   VAR satisfies stability condition.

.
. varlmar

   Lagrange-multiplier test
  +--------------------------------------+
  | lag  |      chi2    df   Prob > chi2 |
  |------+-------------------------------|
  |   1  |    7.3918     9     0.59639   |
  |   2  |    7.1825     9     0.61812   |
  +--------------------------------------+
   H0: no autocorrelation at lag order


pre DCEclose, CBOTopen, spot CNNT
. varsoc ldlnCBOTopen dlnDCEclose dlnspot

   Selection-order criteria
   Sample:  7 - 578                           Number of obs      =       572
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  5712.05                        4.3e-13  -19.9617  -19.9528  -19.9389  |
  |  1 |  5773.52  122.94    9  0.000  3.6e-13  -20.1452  -20.1096* -20.0539* |
  |  2 |  5785.04  23.049*   9  0.006  3.5e-13*  -20.154* -20.0917  -19.9943  |
  |  3 |  5789.43  8.7825    9  0.458  3.6e-13  -20.1379  -20.0489  -19.9098  |
  |  4 |  5795.62  12.364    9  0.194  3.6e-13   -20.128  -20.0123  -19.8315  |
  +---------------------------------------------------------------------------+
   Endogenous:  ldlnCBOTopen dlnDCEclose dlnspot
    Exogenous:  _cons

. var ldlnCBOTopen dlnDCEclose dlnspot, lag(1/2)
```

```
Vector autoregression

Sample:  5 - 578                                   No. of obs      =       574
Log likelihood =  5806.973                         AIC             = -20.16018
FPE            =  3.52e-13                         HQIC            = -20.09807
Det(Sigma_ml)  =  3.28e-13                         SBIC            = -20.00094

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
ldlnCBOTopen         7     .010786   0.2085   151.2078   0.0000
dlnDCEclose          7     .011377   0.0150   8.763034   0.1874
dlnspot              7     .004954   0.0095   5.523348   0.4786
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ldlnCBOTopen |
ldlnCBOTopen |
         L1. |  -.1084136   .0415327    -2.61   0.009    -.1898162    -.027011
         L2. |   .0406689   .0377329     1.08   0.281    -.0332863     .114624
             |
 dlnDCEclose |
         L1. |   .2875254    .040869     7.04   0.000     .2074236    .3676272
         L2. |   .1610606   .0426229     3.78   0.000     .0775214    .2445999
             |
     dlnspot |
         L1. |   .6316124   .0947419     6.67   0.000     .4459218     .817303
         L2. |  -.1352079   .0982472    -1.38   0.169    -.3277689     .057353
             |
       _cons |   .0000852   .0004484     0.19   0.849    -.0007936    .0009639
-------------+----------------------------------------------------------------
dlnDCEclose  |
ldlnCBOTopen |
         L1. |    .019505   .0438062     0.45   0.656    -.0663535    .1053635
         L2. |  -.0013136   .0397984    -0.03   0.974    -.0793171    .0766898
             |
 dlnDCEclose |
         L1. |   .0447557   .0431061     1.04   0.299    -.0397308    .1292422
         L2. |  -.1232718    .044956    -2.74   0.006    -.2113839   -.0351596
             |
     dlnspot |
         L1. |  -.0277774   .0999279    -0.28   0.781    -.2236325    .1680778
         L2. |   .0191406   .1036251     0.18   0.853    -.1839609    .2222422
             |
       _cons |    .000032   .0004729     0.07   0.946    -.0008949    .0009589
-------------+----------------------------------------------------------------
dlnspot      |
ldlnCBOTopen |
         L1. |   .0196753   .0190752     1.03   0.302    -.0177115    .0570621
         L2. |   .0078935   .0173301     0.46   0.649    -.0260728    .0418599
             |
 dlnDCEclose |
         L1. |   .0263385   .0187704     1.40   0.161    -.0104509    .0631278
         L2. |  -.0139941   .0195759    -0.71   0.475    -.0523623     .024374
             |
     dlnspot |
         L1. |   .0443889   .0435133     1.02   0.308    -.0408956    .1296733
         L2. |   -.008297   .0451232    -0.18   0.854    -.0967369    .0801428
             |
       _cons |   .0002107   .0002059     1.02   0.306    -.0001929    .0006143
------------------------------------------------------------------------------
```

```
.
. vargranger

   Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |      ldlnCBOTopen        dlnDCEclose |      66     2    0.000     |
  |      ldlnCBOTopen            dlnspot |  45.966     2    0.000     |
  |      ldlnCBOTopen                ALL |  148.14     4    0.000     |
  |--------------------------------------+---------------------------|
  |       dlnDCEclose       ldlnCBOTopen |  .20318     2    0.903     |
  |       dlnDCEclose            dlnspot |  .10924     2    0.947     |
  |       dlnDCEclose                ALL |  .34829     4    0.986     |
  |--------------------------------------+---------------------------|
  |           dlnspot       ldlnCBOTopen |  1.2017     2    0.548     |
  |           dlnspot        dlnDCEclose |  2.4038     2    0.301     |
  |           dlnspot                ALL |  3.1662     4    0.530     |
  +------------------------------------------------------------------+

.
. varstable, graph

   Eigenvalue stability condition
  +----------------------------------------+
  |        Eigenvalue        |   Modulus   |
  |--------------------------+-------------|
  |  .01667889 +   .336508i  |   .336921   |
  |  .01667889 -   .336508i  |   .336921   |
  |  -.2039665               |   .203967   |
  |   .1388886 + .02928731i  |   .141943   |
  |   .1388886 - .02928731i  |   .141943   |
  |  -.1264374               |   .126437   |
  +----------------------------------------+
   All the eigenvalues lie inside the unit circle.
   VAR satisfies stability condition.

.
. varlmar

   Lagrange-multiplier test
  +--------------------------------------+
  | lag  |      chi2    df   Prob > chi2 |
  |------+-------------------------------|
  |   1  |    6.3530     9     0.70413   |
  |   2  |    4.2853     9     0.89165   |
  +--------------------------------------+
   H0: no autocorrelation at lag order
```

after DCEclose, CBOTopen, spot CNQD
still do validation test to ensure the model is set properly

```
. varsoc ldlnCBOTopen dlnDCEclose dlnspot

   Selection-order criteria
   Sample:  585 - 733                          Number of obs      =       149
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  1506.56                      3.4e-13* -20.1821* -20.1575* -20.1216* |
```

```
  |  1 |  1511.29  9.4468    9  0.397  3.7e-13  -20.1247  -20.0264  -19.8827  |
  |  2 |  1513.22  3.8681    9  0.920  4.0e-13  -20.0298  -19.8578  -19.6064  |
  |  3 |  1516.83  7.2252    9  0.614  4.3e-13  -19.9575  -19.7118  -19.3527  |
  |  4 |  1524.74  15.807    9  0.071  4.4e-13  -19.9428  -19.6233  -19.1565  |
  +---------------------------------------------------------------------------+
   Endogenous:  ldlnCBOTopen dlnDCEclose dlnspot
    Exogenous:  _cons

.
. var ldlnCBOTopen dlnDCEclose dlnspot, lag(1)

Vector autoregression

Sample:  582 - 733                                 No. of obs      =       152
Log likelihood =  1543.121                         AIC             = -20.14633
FPE            =  3.57e-13                         HQIC            = -20.04936
Det(Sigma_ml)  =  3.05e-13                         SBIC            = -19.90761

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
ldlnCBOTopen          4     .012587   0.0465   7.416215   0.0598
dlnDCEclose           4      .01164   0.0102   1.566789   0.6669
dlnspot               4     .003978   0.0104    1.60361   0.6586
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ldlnCBOTopen |
ldlnCBOTopen |
         L1. |  -.1131643   .0791994    -1.43   0.153    -.2683922    .0420637
             |
 dlnDCEclose |
         L1. |   .1495054   .0884133     1.69   0.091    -.0237815    .3227923
             |
     dlnspot |
         L1. |   .3173953   .2584497     1.23   0.219    -.1891568    .8239474
             |
       _cons |   .0002574   .0010163     0.25   0.800    -.0017345    .0022492
-------------+----------------------------------------------------------------
dlnDCEclose  |
ldlnCBOTopen |
         L1. |   .0168408   .0732433     0.23   0.818    -.1267135    .1603952
             |
 dlnDCEclose |
         L1. |  -.0432714   .0817644    -0.53   0.597    -.2035266    .1169838
             |
     dlnspot |
         L1. |  -.2420463   .2390135    -1.01   0.311    -.7105041    .2264115
             |
       _cons |  -.0007016   .0009399    -0.75   0.455    -.0025437    .0011405
-------------+----------------------------------------------------------------
dlnspot      |
ldlnCBOTopen |
         L1. |  -.0118773   .0250329    -0.47   0.635    -.0609409    .0371862
             |
 dlnDCEclose |
         L1. |  -.0263738   .0279452    -0.94   0.345    -.0811453    .0283978
             |
     dlnspot |
         L1. |  -.0465453   .0816893    -0.57   0.569    -.2066533    .1135628
             |
       _cons |   -.000545   .0003212    -1.70   0.090    -.0011746    .0000846
```

---

.
. vargranger

Granger causality Wald tests

| Equation | Excluded | chi2 | df | Prob > chi2 |
|---|---|---|---|---|
| ldlnCBOTopen | dlnDCEclose | 2.8594 | 1 | 0.091 |
| ldlnCBOTopen | dlnspot | 1.5082 | 1 | 0.219 |
| ldlnCBOTopen | ALL | 5.1425 | 2 | 0.076 |
| dlnDCEclose | ldlnCBOTopen | .05287 | 1 | 0.818 |
| dlnDCEclose | dlnspot | 1.0255 | 1 | 0.311 |
| dlnDCEclose | ALL | 1.0634 | 2 | 0.588 |
| dlnspot | ldlnCBOTopen | .22512 | 1 | 0.635 |
| dlnspot | dlnDCEclose | .8907 | 1 | 0.345 |
| dlnspot | ALL | 1.0607 | 2 | 0.588 |

.
. varstable, graph

Eigenvalue stability condition

| Eigenvalue | Modulus |
|---|---|
| -.1226479 + .04882223i | .132008 |
| -.1226479 - .04882223i | .132008 |
| .04231485 | .042315 |

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition.

.
. varlmar

Lagrange-multiplier test

| lag | chi2 | df | Prob > chi2 |
|---|---|---|---|
| 1 | 4.4236 | 9 | 0.88139 |
| 2 | 3.3581 | 9 | 0.94839 |

H0: no autocorrelation at lag order

after DCEclose, CBOTopen, spot CNSH
do validation test to ensure the model is set properly

. varsoc ldlnCBOTopen dlnDCEclose dlnspot

Selection-order criteria
Sample: 585 - 733 Number of obs = 149

| lag | LL | LR | df | p | FPE | AIC | HQIC | SBIC |
|---|---|---|---|---|---|---|---|---|
| 0 | 1506.56 | | | | 3.4e-13* | -20.1821* | -20.1575* | -20.1216* |
| 1 | 1511.29 | 9.4468 | 9 | 0.397 | 3.7e-13 | -20.1247 | -20.0264 | -19.8827 |
| 2 | 1513.22 | 3.8681 | 9 | 0.920 | 4.0e-13 | -20.0298 | -19.8578 | -19.6064 |

```
  |  3 |  1516.83  7.2252    9  0.614  4.3e-13  -19.9575  -19.7118  -19.3527  |
  |  4 |  1524.74  15.807    9  0.071  4.4e-13  -19.9428  -19.6233  -19.1565  |
  +---------------------------------------------------------------------------+
   Endogenous:  ldlnCBOTopen dlnDCEclose dlnspot
    Exogenous:  _cons

.
. var ldlnCBOTopen dlnDCEclose dlnspot, lag(1)

Vector autoregression

Sample:  582 - 733                               No. of obs      =       152
Log likelihood =  1543.121                       AIC             = -20.14633
FPE            =  3.57e-13                       HQIC            = -20.04936
Det(Sigma_ml)  =  3.05e-13                       SBIC            = -19.90761

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
ldlnCBOTopen          4     .012587   0.0465   7.416215   0.0598
dlnDCEclose           4      .01164   0.0102   1.566789   0.6669
dlnspot               4     .003978   0.0104    1.60361   0.6586
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ldlnCBOTopen |
ldlnCBOTopen |
         L1. |  -.1131643   .0791994    -1.43   0.153    -.2683922    .0420637
             |
 dlnDCEclose |
         L1. |   .1495054   .0884133     1.69   0.091    -.0237815    .3227923
             |
     dlnspot |
         L1. |   .3173953   .2584497     1.23   0.219    -.1891568    .8239474
             |
       _cons |   .0002574   .0010163     0.25   0.800    -.0017345    .0022492
-------------+----------------------------------------------------------------
dlnDCEclose  |
ldlnCBOTopen |
         L1. |   .0168408   .0732433     0.23   0.818    -.1267135    .1603952
             |
 dlnDCEclose |
         L1. |  -.0432714   .0817644    -0.53   0.597    -.2035266    .1169838
             |
     dlnspot |
         L1. |  -.2420463   .2390135    -1.01   0.311    -.7105041    .2264115
             |
       _cons |  -.0007016   .0009399    -0.75   0.455    -.0025437    .0011405
-------------+----------------------------------------------------------------
dlnspot      |
ldlnCBOTopen |
         L1. |  -.0118773   .0250329    -0.47   0.635    -.0609409    .0371862
             |
 dlnDCEclose |
         L1. |  -.0263738   .0279452    -0.94   0.345    -.0811453    .0283978
             |
     dlnspot |
         L1. |  -.0465453   .0816893    -0.57   0.569    -.2066533    .1135628
             |
       _cons |   -.000545   .0003212    -1.70   0.090    -.0011746    .0000846
------------------------------------------------------------------------------
```

```
.
. vargranger

   Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |      ldlnCBOTopen        dlnDCEclose |  2.8594     1    0.091    |
  |      ldlnCBOTopen            dlnspot |  1.5082     1    0.219    |
  |      ldlnCBOTopen                ALL |  5.1425     2    0.076    |
  |--------------------------------------+---------------------------|
  |       dlnDCEclose       ldlnCBOTopen |  .05287     1    0.818    |
  |       dlnDCEclose            dlnspot |  1.0255     1    0.311    |
  |       dlnDCEclose                ALL |  1.0634     2    0.588    |
  |--------------------------------------+---------------------------|
  |           dlnspot       ldlnCBOTopen |  .22512     1    0.635    |
  |           dlnspot        dlnDCEclose |   .8907     1    0.345    |
  |           dlnspot                ALL |  1.0607     2    0.588    |
  +------------------------------------------------------------------+

.
. varstable, graph

   Eigenvalue stability condition
  +----------------------------------------+
  |        Eigenvalue        |   Modulus   |
  |--------------------------+-------------|
  |  -.1226479 + .04882223i  |   .132008   |
  |  -.1226479 - .04882223i  |   .132008   |
  |  .04231485               |   .042315   |
  +----------------------------------------+
   All the eigenvalues lie inside the unit circle.
   VAR satisfies stability condition.

.
. varlmar

   Lagrange-multiplier test
  +--------------------------------------+
  | lag  |      chi2    df   Prob > chi2 |
  |------+-------------------------------|
  |   1  |    4.4236     9     0.88139   |
  |   2  |    3.3581     9     0.94839   |
  +--------------------------------------+
   H0: no autocorrelation at lag order


after DCEclose, CBOTopen, spot CNNT
still do validation test to ensure the model is set properly


. varsoc ldlnCBOTopen dlnDCEclose dlnspot

   Selection-order criteria
   Sample:  585 - 733                          Number of obs      =       149
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  1506.56                      3.4e-13* -20.1821* -20.1575* -20.1216* |
  |  1 |  1511.29  9.4468    9  0.397  3.7e-13  -20.1247  -20.0264  -19.8827  |
  |  2 |  1513.22  3.8681    9  0.920  4.0e-13  -20.0298  -19.8578  -19.6064  |
  |  3 |  1516.83  7.2252    9  0.614  4.3e-13  -19.9575  -19.7118  -19.3527  |
```

```
  |  4 |  1524.74  15.807    9  0.071  4.4e-13  -19.9428  -19.6233  -19.1565  |
  +---------------------------------------------------------------------------+
   Endogenous:  ldlnCBOTopen dlnDCEclose dlnspot
    Exogenous:  _cons

.
. var ldlnCBOTopen dlnDCEclose dlnspot, lag(1)

Vector autoregression

Sample:  582 - 733                                 No. of obs      =       152
Log likelihood =  1543.121                         AIC             = -20.14633
FPE            =  3.57e-13                         HQIC            = -20.04936
Det(Sigma_ml)  =  3.05e-13                         SBIC            = -19.90761

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
ldlnCBOTopen          4     .012587   0.0465   7.416215   0.0598
dlnDCEclose           4      .01164   0.0102   1.566789   0.6669
dlnspot               4     .003978   0.0104    1.60361   0.6586
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ldlnCBOTopen |
ldlnCBOTopen |
         L1. |  -.1131643   .0791994    -1.43   0.153    -.2683922    .0420637
             |
 dlnDCEclose |
         L1. |   .1495054   .0884133     1.69   0.091    -.0237815    .3227923
             |
     dlnspot |
         L1. |   .3173953   .2584497     1.23   0.219    -.1891568    .8239474
             |
       _cons |   .0002574   .0010163     0.25   0.800    -.0017345    .0022492
-------------+----------------------------------------------------------------
dlnDCEclose  |
ldlnCBOTopen |
         L1. |   .0168408   .0732433     0.23   0.818    -.1267135    .1603952
             |
 dlnDCEclose |
         L1. |  -.0432714   .0817644    -0.53   0.597    -.2035266    .1169838
             |
     dlnspot |
         L1. |  -.2420463   .2390135    -1.01   0.311    -.7105041    .2264115
             |
       _cons |  -.0007016   .0009399    -0.75   0.455    -.0025437    .0011405
-------------+----------------------------------------------------------------
dlnspot      |
ldlnCBOTopen |
         L1. |  -.0118773   .0250329    -0.47   0.635    -.0609409    .0371862
             |
 dlnDCEclose |
         L1. |  -.0263738   .0279452    -0.94   0.345    -.0811453    .0283978
             |
     dlnspot |
         L1. |  -.0465453   .0816893    -0.57   0.569    -.2066533    .1135628
             |
       _cons |   -.000545   .0003212    -1.70   0.090    -.0011746    .0000846
------------------------------------------------------------------------------

.
```

```
. vargranger

   Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |      ldlnCBOTopen        dlnDCEclose |  2.8594     1    0.091    |
  |      ldlnCBOTopen            dlnspot |  1.5082     1    0.219    |
  |      ldlnCBOTopen                ALL |  5.1425     2    0.076    |
  |--------------------------------------+---------------------------|
  |       dlnDCEclose       ldlnCBOTopen |  .05287     1    0.818    |
  |       dlnDCEclose            dlnspot |  1.0255     1    0.311    |
  |       dlnDCEclose                ALL |  1.0634     2    0.588    |
  |--------------------------------------+---------------------------|
  |           dlnspot       ldlnCBOTopen |  .22512     1    0.635    |
  |           dlnspot        dlnDCEclose |   .8907     1    0.345    |
  |           dlnspot                ALL |  1.0607     2    0.588    |
  +------------------------------------------------------------------+

.
. varstable, graph

   Eigenvalue stability condition
  +----------------------------------------+
  |        Eigenvalue        |   Modulus   |
  |--------------------------+-------------|
  |  -.1226479 + .04882223i  |   .132008   |
  |  -.1226479 - .04882223i  |   .132008   |
  |  .04231485               |   .042315   |
  +----------------------------------------+
   All the eigenvalues lie inside the unit circle.
   VAR satisfies stability condition.

.
. varlmar

   Lagrange-multiplier test
  +--------------------------------------+
  | lag  |      chi2    df   Prob > chi2 |
  |------+-------------------------------|
  |   1  |    4.4236     9     0.88139   |
  |   2  |    3.3581     9     0.94839   |
  +--------------------------------------+
   H0: no autocorrelation at lag order
```

pre war settle spotCNQD

```
. varsoc dlnCBOTsettle dlnDCEsettle dlnspot

   Selection-order criteria
   Sample:  6 - 583                            Number of obs      =       578
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  5783.36                        4.1e-13  -20.0012  -19.9924  -19.9786  |
  |  1 |  5833.88  101.04    9  0.000  3.6e-13  -20.1449  -20.1096* -20.0544* |
  |  2 |  5844.25  20.747    9  0.014  3.6e-13  -20.1497  -20.0879  -19.9913  |
  |  3 |     5855  21.484*   9  0.011  3.5e-13* -20.1557* -20.0675  -19.9294  |
  |  4 |  5860.35  10.715    9  0.296  3.6e-13  -20.1431  -20.0284  -19.8489  |
  +---------------------------------------------------------------------------+
   Endogenous:  dlnCBOTsettle dlnDCEsettle dlnspot
```

```
    Exogenous:  _cons

. var dlnCBOTsettle dlnDCEsettle dlnspot, lag(1/3)

Vector autoregression

Sample:  5 - 583                                   No. of obs      =       579
Log likelihood =    5866.6                         AIC             = -20.16097
FPE            =  3.52e-13                         HQIC            = -20.07286
Det(Sigma_ml)  =  3.18e-13                         SBIC            = -19.93499

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dlnCBOTsettle        10     .013247   0.0275   16.39199   0.0591
dlnDCEsettle         10     .009408   0.1421   95.90739   0.0000
dlnspot              10     .004962   0.0768   48.14117   0.0000
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dlnCBOTsettle |
dlnCBOTsettle |
          L1. |   -.134813   .0420967    -3.20   0.001    -.2173209    -.052305
          L2. |  -.0165871   .0452465    -0.37   0.714    -.1052686    .0720943
          L3. |   .0148364   .0447098     0.33   0.740    -.0727931     .102466
              |
 dlnDCEsettle |
          L1. |   .0070322   .0614655     0.11   0.909     -.113438    .1275025
          L2. |    .064338   .0618599     1.04   0.298    -.0569052    .1855812
          L3. |  -.1248177   .0590948    -2.11   0.035    -.2406415    -.008994
              |
      dlnspot |
          L1. |   .0263075   .1167422     0.23   0.822     -.202503    .2551179
          L2. |  -.0920554   .1160435    -0.79   0.428    -.3194964    .1353856
          L3. |   .0519355   .1148374     0.45   0.651    -.1731416    .2770126
              |
        _cons |   .0001526   .0005473     0.28   0.780      -.00092    .0012253
-------------+----------------------------------------------------------------
dlnDCEsettle  |
dlnCBOTsettle |
          L1. |   .2249717   .0298971     7.52   0.000     .1663746    .2835689
          L2. |   .0153523   .0321341     0.48   0.633    -.0476293    .0783338
          L3. |   .0288678   .0317529     0.91   0.363    -.0333667    .0911024
              |
 dlnDCEsettle |
          L1. |   .1654248   .0436528     3.79   0.000     .0798668    .2509828
          L2. |  -.1154948   .0439329    -2.63   0.009    -.2016018   -.0293879
          L3. |    .063168   .0419692     1.51   0.132      -.01909    .1454261
              |
      dlnspot |
          L1. |  -.0880737   .0829103    -1.06   0.288    -.2505749    .0744275
          L2. |  -.1228846   .0824141    -1.49   0.136    -.2844133    .0386441
          L3. |   .1852002   .0815575     2.27   0.023     .0253504      .34505
              |
        _cons |  -.0000168   .0003887    -0.04   0.965    -.0007786     .000745
------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dlnspot       |
dlnCBOTsettle |
          L1. |   .0954857   .0157695     6.06   0.000      .064578    .1263933
          L2. |   .0546533   .0169494     3.22   0.001      .021433    .0878735
```

```
         L3. |   .0257825   .0167484     1.54   0.124    -.0070437    .0586087
             |
dlnDCEsettle |
         L1. |  -.0311484   .0230251    -1.35   0.176    -.0762768      .01398
         L2. |  -.0237187   .0231729    -1.02   0.306    -.0691366    .0216993
         L3. |  -.0103285   .0221371    -0.47   0.641    -.0537163    .0330594
             |
     dlnspot |
         L1. |   .0306392   .0437319     0.70   0.484    -.0550737    .1163521
         L2. |  -.0114407   .0434701    -0.26   0.792    -.0966406    .0737592
         L3. |   .0709762   .0430183     1.65   0.099    -.0133381    .1552906
             |
       _cons |   .0001742    .000205     0.85   0.395    -.0002276     .000576
------------------------------------------------------------------------------

.
. vargranger

   Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |     dlnCBOTsettle       dlnDCEsettle |  5.1505     3    0.161    |
  |     dlnCBOTsettle            dlnspot |  .82396     3    0.844    |
  |     dlnCBOTsettle                ALL |  5.5305     6    0.478    |
  |--------------------------------------+---------------------------|
  |      dlnDCEsettle      dlnCBOTsettle |  58.244     3    0.000    |
  |      dlnDCEsettle            dlnspot |  8.1003     3    0.044    |
  |      dlnDCEsettle                ALL |  64.477     6    0.000    |
  |--------------------------------------+---------------------------|
  |           dlnspot      dlnCBOTsettle |  42.119     3    0.000    |
  |           dlnspot       dlnDCEsettle |  3.7109     3    0.294    |
  |           dlnspot                ALL |  42.658     6    0.000    |
  +------------------------------------------------------------------+

.
. varstable, graph

   Eigenvalue stability condition
  +----------------------------------------+
  |        Eigenvalue        |   Modulus   |
  |--------------------------+-------------|
  |  -.1712259 +  .4616005i  |   .492335   |
  |  -.1712259 -  .4616005i  |   .492335   |
  |    .454273 +  .1574511i  |   .480786   |
  |    .454273 -  .1574511i  |   .480786   |
  |   -.288084 +  .3792512i  |    .47626   |
  |   -.288084 -  .3792512i  |    .47626   |
  |     .14871 +   .313205i  |   .346716   |
  |     .14871 -   .313205i  |   .346716   |
  |  -.2260953               |   .226095   |
  +----------------------------------------+
   All the eigenvalues lie inside the unit circle.
   VAR satisfies stability condition.

.
. varlmar

   Lagrange-multiplier test
  +--------------------------------------+
  | lag  |      chi2    df   Prob > chi2 |
  |------+-------------------------------|
  |   1  |    7.3129     9     0.60458   |
```

```
  |   2  |    2.8389     9     0.97034   |
  +--------------------------------------+
   H0: no autocorrelation at lag order
```

pre war settle spotCNSH

```
. varsoc dlnCBOTsettle dlnDCEsettle dlnspot

   Selection-order criteria
   Sample:  6 - 583                            Number of obs      =       578
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  5794.52                      4.0e-13  -20.0399   -20.031  -20.0172  |
  |  1 |  5844.01  98.978    9  0.000  3.5e-13    -20.18  -20.1447* -20.0894* |
  |  2 |  5853.93  19.837    9  0.019  3.4e-13  -20.1831  -20.1214  -20.0247  |
  |  3 |   5865.6  23.339*   9  0.005  3.4e-13* -20.1924* -20.1041  -19.9661  |
  |  4 |  5871.12  11.046    9  0.273  3.5e-13  -20.1803  -20.0656  -19.8862  |
  +---------------------------------------------------------------------------+
   Endogenous:  dlnCBOTsettle dlnDCEsettle dlnspot
    Exogenous:  _cons

. var dlnCBOTsettle dlnDCEsettle dlnspot, lag(1/3)

Vector autoregression

Sample:  5 - 583                                  No. of obs      =       579
Log likelihood =   5877.23                        AIC             = -20.19769
FPE            =  3.39e-13                        HQIC            = -20.10958
Det(Sigma_ml)  =  3.06e-13                        SBIC            = -19.97171

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dlnCBOTsettle        10     .013244   0.0279   16.62508   0.0549
dlnDCEsettle         10      .00941   0.1418   95.66837   0.0000
dlnspot              10     .004875   0.0756   47.35729   0.0000
----------------------------------------------------------------

------------------------------------------------------------------------------
              |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+---------------------------------------------------------------
dlnCBOTsettle |
dlnCBOTsettle |
          L1. |  -.1347095   .0420585    -3.20   0.001    -.2171426   -.0522764
          L2. |  -.0181579   .0450777    -0.40   0.687    -.1065086    .0701927
          L3. |   .0129253   .0445507     0.29   0.772    -.0743925    .1002431
              |
 dlnDCEsettle |
          L1. |    .003315   .0616121     0.05   0.957    -.1174424    .1240725
          L2. |   .0664331    .062046     1.07   0.284    -.0551748     .188041
          L3. |  -.1270966   .0592503    -2.15   0.032     -.243225   -.0109682
              |
      dlnspot |
          L1. |   .0479469   .1186468     0.40   0.686    -.1845964    .2804903
          L2. |  -.0947599    .118165    -0.80   0.423    -.3263592    .1368393
          L3. |   .0686396   .1175349     0.58   0.559    -.1617245    .2990037
              |
        _cons |   .0001452    .000547     0.27   0.791    -.0009268    .0012173
--------------+---------------------------------------------------------------
dlnDCEsettle  |
dlnCBOTsettle |
```

```
         L1. |   .2252772   .0298811     7.54   0.000     .1667113     .283843
         L2. |   .0140202   .0320261     0.44   0.662    -.0487499    .0767903
         L3. |   .0282751   .0316517     0.89   0.372    -.0337611    .0903114
             |
 dlnDCEsettle |
         L1. |   .1671398   .0437732     3.82   0.000     .0813459    .2529338
         L2. |  -.1153201   .0440815    -2.62   0.009    -.2017182   -.0289219
         L3. |    .062896   .0420952     1.49   0.135    -.0196092    .1454012
             |
      dlnspot |
         L1. |  -.1039603   .0842944    -1.23   0.217    -.2691742    .0612537
         L2. |  -.1147875   .0839521    -1.37   0.172    -.2793307    .0497556
         L3. |   .1842686   .0835044     2.21   0.027      .020603    .3479342
             |
        _cons |  -.0000175   .0003886    -0.04   0.964    -.0007791    .0007442
--------------+----------------------------------------------------------------
dlnspot       |
dlnCBOTsettle |
         L1. |    .087855   .0154811     5.67   0.000     .0575126    .1181974
         L2. |   .0521115   .0165924     3.14   0.002     .0195909     .084632
         L3. |   .0297138   .0163984     1.81   0.070    -.0024266    .0618541
             |
 dlnDCEsettle |
         L1. |  -.0256733   .0226785    -1.13   0.258    -.0701223    .0187757
         L2. |  -.0348755   .0228382    -1.53   0.127    -.0796375    .0098866
         L3. |  -.0159084   .0218091    -0.73   0.466    -.0586535    .0268367
             |
      dlnspot |
         L1. |   .0367213   .0436721     0.84   0.400    -.0488744     .122317
         L2. |  -.0094635   .0434948    -0.22   0.828    -.0947117    .0757847
         L3. |   .0918448   .0432628     2.12   0.034     .0070512    .1766383
             |
        _cons |   .0001474   .0002013     0.73   0.464    -.0002472     .000542
-------------------------------------------------------------------------------

.
. vargranger

   Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |     dlnCBOTsettle       dlnDCEsettle |  5.2703     3    0.153    |
  |     dlnCBOTsettle            dlnspot |   1.051     3    0.789    |
  |     dlnCBOTsettle                ALL |  5.7594     6    0.451    |
  |--------------------------------------+---------------------------|
  |      dlnDCEsettle      dlnCBOTsettle |  58.492     3    0.000    |
  |      dlnDCEsettle            dlnspot |  7.8924     3    0.048    |
  |      dlnDCEsettle                ALL |  64.249     6    0.000    |
  |--------------------------------------+---------------------------|
  |           dlnspot      dlnCBOTsettle |  38.326     3    0.000    |
  |           dlnspot       dlnDCEsettle |  5.1164     3    0.163    |
  |           dlnspot                ALL |  39.863     6    0.000    |
  +------------------------------------------------------------------+

.
. varstable, graph

   Eigenvalue stability condition
  +----------------------------------------+
  |        Eigenvalue        |   Modulus   |
  |--------------------------+-------------|
  |  -.1610516 +  .4839486i  |    .510043  |
```

```
  |  -.1610516 -  .4839486i  |   .510043   |
  |  -.3023295 +  .3918791i  |   .494947   |
  |  -.3023295 -  .3918791i  |   .494947   |
  |   .4688596 +  .1450089i  |   .490772   |
  |   .4688596 -  .1450089i  |   .490772   |
  |   .1484673 +   .300842i  |   .335482   |
  |   .1484673 -   .300842i  |   .335482   |
  |  -.2387399               |    .23874   |
  +----------------------------------------+
   All the eigenvalues lie inside the unit circle.
   VAR satisfies stability condition.

.
. varlmar

   Lagrange-multiplier test
  +--------------------------------------+
  | lag  |      chi2    df   Prob > chi2 |
  |------+-------------------------------|
  |   1  |    7.9708     9     0.53709   |
  |   2  |    3.3062     9     0.95091   |
  +--------------------------------------+
   H0: no autocorrelation at lag order
```

pre war settle spotCNNT

```
. varsoc dlnCBOTsettle dlnDCEsettle dlnspot

   Selection-order criteria
   Sample:  6 - 583                            Number of obs      =       578
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  5804.8                        3.8e-13  -20.0754  -20.0666  -20.0528  |
  |  1 |  5853.16  96.706    9  0.000  3.3e-13  -20.2116  -20.1763* -20.1211* |
  |  2 |  5863.33  20.345    9  0.016  3.3e-13  -20.2157  -20.1539  -20.0573  |
  |  3 |  5874.98    23.3*   9  0.006  3.3e-13* -20.2248* -20.1366  -19.9986  |
  |  4 |  5881.21  12.461    9  0.189  3.3e-13  -20.2153  -20.1006  -19.9211  |
  +---------------------------------------------------------------------------+
   Endogenous:  dlnCBOTsettle dlnDCEsettle dlnspot
    Exogenous:  _cons

.
. var dlnCBOTsettle dlnDCEsettle dlnspot, lag(1/3)

Vector autoregression

Sample:  5 - 583                                  No. of obs      =       579
Log likelihood =  5886.617                        AIC             = -20.23011
FPE            =  3.29e-13                        HQIC            = -20.14201
Det(Sigma_ml)  =  2.96e-13                        SBIC            = -20.00414

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dlnCBOTsettle        10     .013245   0.0279   16.60025   0.0554
dlnDCEsettle         10     .009426   0.1388   93.30775   0.0000
dlnspot              10     .004744   0.0771   48.39244   0.0000
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

```
dlnCBOTsettle |
dlnCBOTsettle |
          L1. |  -.1355354   .0420575    -3.22   0.001    -.2179666   -.0531043
          L2. |  -.0199905   .0450595    -0.44   0.657    -.1083055    .0683245
          L3. |   .0120484    .044564     0.27   0.787    -.0752955    .0993923
              |
 dlnDCEsettle |
          L1. |  -.0022602   .0610295    -0.04   0.970    -.1218758    .1173553
          L2. |   .0638589    .061367     1.04   0.298    -.0564182    .1841361
          L3. |    -.11386   .0586799    -1.94   0.052    -.2288705    .0011506
              |
      dlnspot |
          L1. |   .0861576   .1206947     0.71   0.475    -.1503996    .3227148
          L2. |  -.0906036   .1199792    -0.76   0.450    -.3257585    .1445512
          L3. |   .0054005   .1190934     0.05   0.964    -.2280183    .2388192
              |
        _cons |   .0001505   .0005473     0.27   0.783    -.0009223    .0012232
--------------+----------------------------------------------------------------
dlnDCEsettle  |
dlnCBOTsettle |
          L1. |   .2245496   .0299322     7.50   0.000     .1658836    .2832155
          L2. |   .0109454   .0320687     0.34   0.733    -.0519081    .0737988
          L3. |   .0267691   .0317161     0.84   0.399    -.0353932    .0889315
              |
 dlnDCEsettle |
          L1. |   .1603641   .0434345     3.69   0.000     .0752341    .2454941
          L2. |  -.1191146   .0436747    -2.73   0.006    -.2047155   -.0335138
          L3. |    .068746   .0417623     1.65   0.100    -.0131066    .1505986
              |
      dlnspot |
          L1. |  -.0706643    .085898    -0.82   0.411    -.2390212    .0976927
          L2. |  -.0957878   .0853888    -1.12   0.262    -.2631467    .0715711
          L3. |   .1733846   .0847583     2.05   0.041     .0072613    .3395079
              |
        _cons |  -.0000225   .0003895    -0.06   0.954     -.000786    .0007409
--------------+----------------------------------------------------------------
dlnspot       |
dlnCBOTsettle |
          L1. |   .0839068   .0150637     5.57   0.000     .0543826    .1134311
          L2. |   .0531613   .0161389     3.29   0.001     .0215296     .084793
          L3. |   .0308067   .0159615     1.93   0.054    -.0004772    .0620905
              |
 dlnDCEsettle |
          L1. |  -.0156073   .0218589    -0.71   0.475    -.0584499    .0272353
          L2. |  -.0424372   .0219798    -1.93   0.054    -.0855167    .0006423
          L3. |  -.0071176   .0210173    -0.34   0.735    -.0483108    .0340756
              |
      dlnspot |
          L1. |   .0307604   .0432291     0.71   0.477    -.0539671    .1154878
          L2. |  -.0096932   .0429728    -0.23   0.822    -.0939184     .074532
          L3. |   .0923156   .0426556     2.16   0.030     .0087123     .175919
              |
        _cons |   .0001701    .000196     0.87   0.386    -.0002141    .0005543
-------------------------------------------------------------------------------

.
. vargranger

   Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |     dlnCBOTsettle       dlnDCEsettle |  4.405     3    0.221     |
```

```
  |     dlnCBOTsettle           dlnspot |  1.0268     3    0.795    |
  |     dlnCBOTsettle               ALL |   5.735     6    0.454    |
  |-----------------------------------+--------------------------|
  |      dlnDCEsettle     dlnCBOTsettle |  58.038     3    0.000    |
  |      dlnDCEsettle           dlnspot |  5.8389     3    0.120    |
  |      dlnDCEsettle               ALL |  61.999     6    0.000    |
  |-----------------------------------+--------------------------|
  |           dlnspot     dlnCBOTsettle |  38.167     3    0.000    |
  |           dlnspot      dlnDCEsettle |  5.0953     3    0.165    |
  |           dlnspot               ALL |  40.478     6    0.000    |
  +--------------------------------------------------------------+

.
. varstable, graph

   Eigenvalue stability condition
  +----------------------------------------+
  |        Eigenvalue        |   Modulus   |
  |--------------------------+-------------|
  |  -.1781068 +  .4977142i  |   .528622   |
  |  -.1781068 -  .4977142i  |   .528622   |
  |   .4551817 +  .1514908i  |   .479729   |
  |   .4551817 -  .1514908i  |   .479729   |
  |  -.2893651 +  .3747931i  |     .4735   |
  |  -.2893651 -  .3747931i  |     .4735   |
  |   .1383166 +  .2615218i  |   .295846   |
  |   .1383166 -  .2615218i  |   .295846   |
  |  -.1964638               |   .196464   |
  +----------------------------------------+
   All the eigenvalues lie inside the unit circle.
   VAR satisfies stability condition.

.
. varlmar

   Lagrange-multiplier test
  +--------------------------------------+
  | lag  |      chi2    df   Prob > chi2 |
  |------+-------------------------------|
  |   1  |   10.0382     9     0.34740   |
  |   2  |    2.5783     9     0.97870   |
  +--------------------------------------+
   H0: no autocorrelation at lag order


after war settle spotCNQD

still do model validation test to ensure model is set properly
. varsoc dlnCBOTsettle dlnDCEsettle dlnspot

   Selection-order criteria
   Sample:  589 - 744                          Number of obs      =       156
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  1621.37                      2.0e-13* -20.7483* -20.7245* -20.6897* |
  |  1 |  1628.09  13.434    9  0.144  2.0e-13   -20.719  -20.6238  -20.4844  |
  |  2 |  1635.66  15.152    9  0.087  2.1e-13  -20.7008    -20.534  -20.2902  |
  |  3 |  1637.51   3.701    9  0.930  2.3e-13  -20.6091  -20.3709  -20.0226  |
  |  4 |  1643.12  11.223    9  0.261  2.4e-13  -20.5657   -20.256  -19.8032  |
  +---------------------------------------------------------------------------+
   Endogenous:  dlnCBOTsettle dlnDCEsettle dlnspot
    Exogenous:  _cons
```

```
.
. var dlnCBOTsettle dlnDCEsettle dlnspot, lag(1)

Vector autoregression

Sample:  586 - 744                              No. of obs      =       159
Log likelihood =  1659.232                      AIC             =  -20.7199
FPE            =  2.01e-13                      HQIC            = -20.62585
Det(Sigma_ml)  =  1.73e-13                      SBIC            = -20.48829

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dlnCBOTsettle         4     .012338   0.0134   2.162058   0.5395
dlnDCEsettle          4      .00957   0.0610   10.33701   0.0159
dlnspot               4     .003709   0.0167   2.707456   0.4390
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dlnCBOTsettle |
dlnCBOTsettle |
          L1. |  -.0967467   .0791745    -1.22   0.222    -.2519259    .0584325
             |
 dlnDCEsettle |
          L1. |   .0691167   .1002274     0.69   0.490    -.1273255    .2655589
             |
      dlnspot |
          L1. |  -.0323739   .2622973    -0.12   0.902    -.5464671    .4817193
             |
        _cons |  -.0000257    .000977    -0.03   0.979    -.0019405    .0018892
-------------+----------------------------------------------------------------
dlnDCEsettle  |
dlnCBOTsettle |
          L1. |   .1670066   .0614116     2.72   0.007     .0466422    .2873711
             |
 dlnDCEsettle |
          L1. |   .1536664   .0777412     1.98   0.048     .0012964    .3060364
             |
      dlnspot |
          L1. |  -.0348538   .2034504    -0.17   0.864    -.4336092    .3639017
             |
        _cons |  -.0005014   .0007578    -0.66   0.508    -.0019867    .0009838
-------------+----------------------------------------------------------------
dlnspot       |
dlnCBOTsettle |
          L1. |   .0190896   .0237994     0.80   0.422    -.0275564    .0657357
             |
 dlnDCEsettle |
          L1. |  -.0395221   .0301278    -1.31   0.190    -.0985716    .0195274
             |
      dlnspot |
          L1. |   .0379079   .0788452     0.48   0.631    -.1166259    .1924416
             |
        _cons |  -.0004985   .0002937    -1.70   0.090    -.0010741    .0000771
------------------------------------------------------------------------------

.
. vargranger

   Granger causality Wald tests
  +------------------------------------------------------------------+
```

```
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |     dlnCBOTsettle      dlnDCEsettle |  .47555     1    0.490     |
  |     dlnCBOTsettle           dlnspot |  .01523     1    0.902     |
  |     dlnCBOTsettle               ALL |  .47686     2    0.788     |
  |--------------------------------------+---------------------------|
  |      dlnDCEsettle     dlnCBOTsettle |  7.3955     1    0.007     |
  |      dlnDCEsettle           dlnspot |  .02935     1    0.864     |
  |      dlnDCEsettle               ALL |  7.4084     2    0.025     |
  |--------------------------------------+---------------------------|
  |           dlnspot     dlnCBOTsettle |  .64337     1    0.422     |
  |           dlnspot      dlnDCEsettle |  1.7209     1    0.190     |
  |           dlnspot               ALL |  2.6019     2    0.272     |
  +------------------------------------------------------------------+

.
. varstable, graph

   Eigenvalue stability condition
  +----------------------------------------+
  |        Eigenvalue        |   Modulus   |
  |--------------------------+-------------|
  |   .2032398               |    .20324   |
  |  -.1311222               |   .131122   |
  |  .02270998               |    .02271   |
  +----------------------------------------+
   All the eigenvalues lie inside the unit circle.
   VAR satisfies stability condition.

.
. varlmar

   Lagrange-multiplier test
  +--------------------------------------+
  | lag  |      chi2    df   Prob > chi2 |
  |------+-------------------------------|
  |   1  |   11.5128     9     0.24219   |
  |   2  |   12.1289     9     0.20614   |
  +--------------------------------------+
   H0: no autocorrelation at lag order
```

after war settle spotCNSH

still do model validation test to ensure model is set properly

```
. varsoc dlnCBOTsettle dlnDCEsettle dlnspot

   Selection-order criteria
   Sample:  589 - 744                           Number of obs      =       156
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  1621.37                      2.0e-13* -20.7483* -20.7245* -20.6897* |
  |  1 |  1628.09  13.434    9  0.144  2.0e-13   -20.719  -20.6238  -20.4844  |
  |  2 |  1635.66  15.152    9  0.087  2.1e-13  -20.7008    -20.534  -20.2902  |
  |  3 |  1637.51   3.701    9  0.930  2.3e-13  -20.6091  -20.3709  -20.0226  |
  |  4 |  1643.12  11.223    9  0.261  2.4e-13  -20.5657    -20.256  -19.8032  |
  +---------------------------------------------------------------------------+
   Endogenous:  dlnCBOTsettle dlnDCEsettle dlnspot
    Exogenous:  _cons
```

```
.
. var dlnCBOTsettle dlnDCEsettle dlnspot, lag(1)

Vector autoregression

Sample:  586 - 744                              No. of obs      =       159
Log likelihood =  1659.232                      AIC             =  -20.7199
FPE            =  2.01e-13                      HQIC            = -20.62585
Det(Sigma_ml)  =  1.73e-13                      SBIC            = -20.48829

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dlnCBOTsettle         4     .012338   0.0134   2.162058   0.5395
dlnDCEsettle          4      .00957   0.0610   10.33701   0.0159
dlnspot               4     .003709   0.0167   2.707456   0.4390
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dlnCBOTsettle |
dlnCBOTsettle |
          L1. |  -.0967467   .0791745    -1.22   0.222    -.2519259    .0584325
             |
 dlnDCEsettle |
          L1. |   .0691167   .1002274     0.69   0.490    -.1273255    .2655589
             |
      dlnspot |
          L1. |  -.0323739   .2622973    -0.12   0.902    -.5464671    .4817193
             |
        _cons |  -.0000257    .000977    -0.03   0.979    -.0019405    .0018892
-------------+----------------------------------------------------------------
dlnDCEsettle  |
dlnCBOTsettle |
          L1. |   .1670066   .0614116     2.72   0.007     .0466422    .2873711
             |
 dlnDCEsettle |
          L1. |   .1536664   .0777412     1.98   0.048     .0012964    .3060364
             |
      dlnspot |
          L1. |  -.0348538   .2034504    -0.17   0.864    -.4336092    .3639017
             |
        _cons |  -.0005014   .0007578    -0.66   0.508    -.0019867    .0009838
-------------+----------------------------------------------------------------
dlnspot       |
dlnCBOTsettle |
          L1. |   .0190896   .0237994     0.80   0.422    -.0275564    .0657357
             |
 dlnDCEsettle |
          L1. |  -.0395221   .0301278    -1.31   0.190    -.0985716    .0195274
             |
      dlnspot |
          L1. |   .0379079   .0788452     0.48   0.631    -.1166259    .1924416
             |
        _cons |  -.0004985   .0002937    -1.70   0.090    -.0010741    .0000771
------------------------------------------------------------------------------

.
. vargranger

   Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
```

```
  |------------------------------------+---------------------------|
  |     dlnCBOTsettle       dlnDCEsettle |  .47555     1    0.490    |
  |     dlnCBOTsettle            dlnspot |  .01523     1    0.902    |
  |     dlnCBOTsettle                ALL |  .47686     2    0.788    |
  |------------------------------------+---------------------------|
  |      dlnDCEsettle      dlnCBOTsettle |  7.3955     1    0.007    |
  |      dlnDCEsettle            dlnspot |  .02935     1    0.864    |
  |      dlnDCEsettle                ALL |  7.4084     2    0.025    |
  |------------------------------------+---------------------------|
  |           dlnspot      dlnCBOTsettle |  .64337     1    0.422    |
  |           dlnspot       dlnDCEsettle |  1.7209     1    0.190    |
  |           dlnspot                ALL |  2.6019     2    0.272    |
  +------------------------------------------------------------------+

.
. varstable, graph

   Eigenvalue stability condition
  +----------------------------------------+
  |        Eigenvalue         |   Modulus   |
  |---------------------------+-------------|
  |   .2032398                |    .20324   |
  |  -.1311222                |   .131122   |
  |  .02270998                |    .02271   |
  +----------------------------------------+
   All the eigenvalues lie inside the unit circle.
   VAR satisfies stability condition.

.
. varlmar

   Lagrange-multiplier test
  +--------------------------------------+
  | lag  |      chi2    df   Prob > chi2 |
  |------+-------------------------------|
  |   1  |   11.5128     9     0.24219   |
  |   2  |   12.1289     9     0.20614   |
  +--------------------------------------+
   H0: no autocorrelation at lag order


after war settle spotCNNT

still do model validation test to ensure model is set properly
. varsoc dlnCBOTsettle dlnDCEsettle dlnspot

   Selection-order criteria
   Sample:  589 - 744                          Number of obs      =       156
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 |  1621.37                      2.0e-13* -20.7483* -20.7245* -20.6897* |
  |  1 |  1628.09  13.434    9  0.144  2.0e-13   -20.719  -20.6238  -20.4844  |
  |  2 |  1635.66  15.152    9  0.087  2.1e-13  -20.7008   -20.534  -20.2902  |
  |  3 |  1637.51   3.701    9  0.930  2.3e-13  -20.6091  -20.3709  -20.0226  |
  |  4 |  1643.12  11.223    9  0.261  2.4e-13  -20.5657   -20.256  -19.8032  |
  +---------------------------------------------------------------------------+
   Endogenous:  dlnCBOTsettle dlnDCEsettle dlnspot
    Exogenous:  _cons

.
. var dlnCBOTsettle dlnDCEsettle dlnspot, lag(1)
```

```
Vector autoregression

Sample:  586 - 744                               No. of obs      =       159
Log likelihood =  1659.232                       AIC             =  -20.7199
FPE            =  2.01e-13                       HQIC            = -20.62585
Det(Sigma_ml)  =  1.73e-13                       SBIC            = -20.48829

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dlnCBOTsettle         4     .012338   0.0134   2.162058   0.5395
dlnDCEsettle          4      .00957   0.0610   10.33701   0.0159
dlnspot               4     .003709   0.0167   2.707456   0.4390
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dlnCBOTsettle |
dlnCBOTsettle |
          L1. |  -.0967467   .0791745    -1.22   0.222    -.2519259    .0584325
              |
 dlnDCEsettle |
          L1. |   .0691167   .1002274     0.69   0.490    -.1273255    .2655589
              |
      dlnspot |
          L1. |  -.0323739   .2622973    -0.12   0.902    -.5464671    .4817193
              |
        _cons |  -.0000257    .000977    -0.03   0.979    -.0019405    .0018892
-------------+----------------------------------------------------------------
dlnDCEsettle  |
dlnCBOTsettle |
          L1. |   .1670066   .0614116     2.72   0.007     .0466422    .2873711
              |
 dlnDCEsettle |
          L1. |   .1536664   .0777412     1.98   0.048     .0012964    .3060364
              |
      dlnspot |
          L1. |  -.0348538   .2034504    -0.17   0.864    -.4336092    .3639017
              |
        _cons |  -.0005014   .0007578    -0.66   0.508    -.0019867    .0009838
-------------+----------------------------------------------------------------
dlnspot       |
dlnCBOTsettle |
          L1. |   .0190896   .0237994     0.80   0.422    -.0275564    .0657357
              |
 dlnDCEsettle |
          L1. |  -.0395221   .0301278    -1.31   0.190    -.0985716    .0195274
              |
      dlnspot |
          L1. |   .0379079   .0788452     0.48   0.631    -.1166259    .1924416
              |
        _cons |  -.0004985   .0002937    -1.70   0.090    -.0010741    .0000771
------------------------------------------------------------------------------

.
. vargranger

   Granger causality Wald tests
  +------------------------------------------------------------------+
  |          Equation           Excluded |   chi2     df Prob > chi2 |
  |--------------------------------------+---------------------------|
  |     dlnCBOTsettle       dlnDCEsettle |  .47555     1    0.490    |
  |     dlnCBOTsettle            dlnspot |  .01523     1    0.902    |
```

```
  |     dlnCBOTsettle                ALL |  .47686     2    0.788     |
  |--------------------------------------+---------------------------|
  |      dlnDCEsettle      dlnCBOTsettle |  7.3955     1    0.007     |
  |      dlnDCEsettle            dlnspot |  .02935     1    0.864     |
  |      dlnDCEsettle                ALL |  7.4084     2    0.025     |
  |--------------------------------------+---------------------------|
  |           dlnspot      dlnCBOTsettle |  .64337     1    0.422     |
  |           dlnspot       dlnDCEsettle |  1.7209     1    0.190     |
  |           dlnspot                ALL |  2.6019     2    0.272     |
  +------------------------------------------------------------------+

.
. varstable, graph

   Eigenvalue stability condition
  +----------------------------------------+
  |        Eigenvalue        |   Modulus   |
  |--------------------------+-------------|
  |   .2032398               |    .20324   |
  |  -.1311222               |   .131122   |
  |  .02270998               |    .02271   |
  +----------------------------------------+
   All the eigenvalues lie inside the unit circle.
   VAR satisfies stability condition.

.
. varlmar

   Lagrange-multiplier test
  +--------------------------------------+
  | lag  |      chi2    df   Prob > chi2 |
  |------+-------------------------------|
  |   1  |   11.5128     9     0.24219   |
  |   2  |   12.1289     9     0.20614   |
  +--------------------------------------+
   H0: no autocorrelation at lag order
```