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Short-Term Impact of the Trade War on U.S. Agricultural Commodities Futures Prices

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Abstract: In this study, I investigate the immediate effects of the U.S.-China trade war on U.S. agricultural futures prices, specifically focusing on five main commodities: soybeans, corn, wheat, rice, and oats. The trade war, initiated in early 2018, led to substantial tariffs being levied by both countries on each other's goods, severely affecting the U.S. agricultural sector. The U.S. government responded with trade aid packages, including the Market Facilitation Programs (MFP), to mitigate farmers' losses. I employ daily futures price data for these grains from 2004 to 2020, alongside comprehensive supply and demand data. Recognizing the non-stationarity in the data, I use the first difference regressions to quantify the price effects of tariffs and government payments. My findings reveal that a 25% Chinese tariff on U.S. soybeans resulted in a significant decrease in soybean and wheat futures prices, highlighting the severe short-term impacts of trade barriers on agricultural markets. Additionally, I show that the substantial payments following the disputes did not effectively support prices.

1. Introduction

In this study, I investigate the immediate effects of the U.S.-China trade war on U.S. agricultural futures prices, specifically focusing on five main commodities, soybeans, corn, wheat, rice, and oats, which were differentially impacted by the imposed tariffs. The trade war, which began in early 2018, resulted in both countries levying substantial tariffs on each other's goods, severely affecting the U.S. agricultural sector, a major contributor to farm income. The U.S. government responded with trade aid packages, including the Market Facilitation Programs (MFP), to mitigate farmers' losses. I employ daily futures price data for five major grains from 2004 to 2020, alongside comprehensive supply and demand data in this study. Recognizing the non-stationarity in the data, I employ the first difference regressions to quantify the price effects of tariffs and government payments to quantify the effects.

In January 2018, the U.S. announced tariffs on solar panels and washing machines, escalating to China-specific trade actions in March to address unfair trade practices and intellectual property theft. By April 4th, China retaliated with 25% tariffs on 106 U.S. products, including soybeans, though this announcement was retracted. Subsequent large cancellations of U.S. soybean orders by China occurred in May. On June 15th, the U.S. imposed 25% tariffs on $50 billion worth of Chinese exports, with $34 billion effective from July 6th. China responded in kind, leading to increased tariffs from 2.6% to 16.6% on a wide range of products, significantly impacting U.S. agricultural exports. From 2018 to 2019, the U.S. agricultural sector faced eight waves of retaliatory tariffs, not only from China but also from Canada, Mexico, the EU, and Turkey.

The U.S. agricultural sector, a major exporter, was severely affected due to several factors: agricultural exports contribute about 20% to U.S. farm income, these products are highly substitutable, allowing importing countries to source from other exporters, and targeting agricultural commodities likely aimed to exert political pressure on the Trump administration. Consequently, U.S. farmers faced lower returns and higher risks. We hypothesize that retaliatory tariffs led to lower U.S. agricultural commodity prices and affected farmers' incomes, aiming to measure this decline to inform policymakers.

To counteract trade damage from ongoing tariff retaliation, the USDA announced trade aid packages totaling up to $28 billion between 2018 and 2019, with the Market Facilitation Programs (MFP) providing the bulk of direct financial compensation to farmers. MFP subsidies significantly increased from just over $4 billion in 2017 to over $20 billion in 2020. Despite the large sums, MFP payments, designed to be decoupled from production to minimize market distortion, theoretically should not have affected prices. However, these subsidies may have influenced storage behavior, potentially alleviating price declines. This study tests the hypothesis that MFP did not significantly impact market prices.Well-developed futures markets enable farmers to hedge against and reduce risk. If a farmer buys futures during the planting season or before storage, she can lock in a certain return and optimize her choice with respect to the profit under certainty. Futures prices and spreads[1] are good predictors of future market spot prices, so futures prices are important indicators of production and storage (e.g., Working, 1949; Pindyck, 1994). Furthermore,

[1] Futures spread is a transaction strategy for buying and selling different futures contracts at the same time, which can be subdivided into inter-commodity, which is a sophisticated options trade that attempts to take advantage of the value differential between two or more related commodities, such as corn and wheat, and intra-commodity spreads, which is futures spread in the same commodity market, with the buy and sell legs spread between different months. Informally, the spread also refers to the price difference between two futures contracts. We use the latter definition in this paper. Specifically, it refers to the futures price on the same commodity of the "near month" minus the "deferred month". The spread is a widely used financial product in the futures market. Shimko (1994) states that spread products satisfy the hedging needs of producers and processors, and work as a speculative tool for traders. It is also equivalent to taking out low-interest loans for farmers through spread trading in some cases. Additionally, the purpose to trade a calendar spread is to profit from the passage of time and an increase in implied volatility. Hence, it is meaningful to study the effect of tariffs on the futures spreads of different lengths.

futures prices are closely correlated with spot prices (e.g., Alquist and Kilian, 2010; Li and Chavas, 2022). Thus, lower futures prices reduce farmers' income. Additionally, futures prices are more responsive to news than spot prices, which make incremental adjustments based on information in the event of a shock. Therefore, we take futures prices as our primary research object.

I collect daily data on the futures prices of five main grains, soybean, corn, wheat, rice, and oats, from 2004 till November 2020 from the Barchart website[2]. I take advantage of the production, use, stock, imports, and exports projections of the U.S. and world's major importers and exporters from the USDA World Agricultural Supply and Demand Estimates (WASDE) reports, aggregated weather data at the national level constructed by PRISM Climate Group, detailed government payment data at the individual level from USDA Farm Service Agency (FSA). I also obtain tariff data of U.S. major agriculture trading partners, including most-favored-nation applied tariffs at the standard codes of the Harmonized Tariff Schedule (HTS) 6 digits level, from the World Trade Organization (WTO).

I carry out a reduced-form regression of future prices (or spreads) on tariffs controlling for weather shocks, monthly projection reports on production, storage, and export by USDA, event dummies of the Covid-19 pandemic outbreak and payments of Coronavirus Food Assistance Program (CFAP), and year and month fixed effects. We construct two time series as our main regressors, one being the tariff rate in effect, the other being the difference between tariff announcement and implementation, for each major trade partner by export value. The two USDA's trade aid packages are also included as separate events or payments to understand the extent to which the policies can influence commodity prices.

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[2] Barchart Website. Available online: https://www.barchart.com/futures/grains.

Since I detect unit roots in futures prices, tariffs, and WASDE report variables, which indicates non-stationarity in the time series data, I take the first order differences of variables on both sides of the equation. Under various specifications, the estimated results are consistently significant, and the magnitude lies in the same ballpark.

The results show that the announcement of a 25% Chinese tariff led to a significant immediate decrease in soybean futures prices by 25.5%, and a smaller 17% decrease upon implementation, indicating that the initial announcement had a more substantial impact. Despite the introduction of tariff exemptions in 2020, the market reaction was negative, with soybean prices falling by 10.59%. Additionally, the study finds that wheat prices were also significantly affected by Chinese tariffs, with a 12.75% decrease upon announcement. Corn and rice experienced negative but not significant effects, while oats remained unaffected due to the U.S. being a major importer rather than an exporter. The impact of USDA's payment programs on prices is inconsistent, with both positive and negative effects that are generally negligible, suggesting that the timing of these payments could play a role. Future research will explore the effect of Market Facilitation Program (MFP) payments on inventory using detailed fund distribution data.

This paper contributes to two strands of literature. First, there is a growing literature on the effects of the trade war, but they focus on the export and import effect of the tariff (Fajgelbaum et al., 2020; Carter and Steinbach, 2020). A few of them examine the price pass-through but do not address agricultural markets or futures markets (Flaaen, Hortaçsu, and Tintelnot, 2020; Cavallo et al., 2020). The studies of the impact of the trade war on agricultural product prices rely on the specification of a process-based model of the U.S. and/or world soybean market. For example, Janzen and Hendricks (2020) estimate the impact of the retaliatory tariff by simulating the change in price with and without a tariff wedge in place. Other studies that measure the trade war impact rely only on prices. For instance, Adjemian et al. (2021) detect structural changes in the price time series, construct a counterfactual price series, and calculate the gap between realized and predicted prices. This paper will estimate the effect empirically and will include a full set of supply and demand covariates instead of using simulation or relying only on the price series.

Second, the quantification and comparison of the effects of USDA financial aid packages will contribute to the agricultural subsidy literature. There is extensive literature on the decoupled farm payments (e.g., Bhaskar and Beghin, 2009). However, this literature focuses more on the production effect of agricultural subsidies (e.g., Goodwin and Mishra, 2006; Olagunju et al., 2020) or the capitalization into land prices (e.g., Ciaian et al., 2021; Guastella et al., 2021). We would like to contribute to this literature by exploring the inventory effect of decoupled agricultural subsidies. What's more, it will facilitate benefit-cost analysis of the policies in the future.

The paper is structured as follows. Section 2 provides the timeline of the trade war. Section 3 proposes a conceptual framework and discusses hypotheses to be tested. Section 4 shows data sources and summary statistics. In Section 5, we quantify the short-term effect of the trade war on futures prices with a reduced-form model. We discuss the results in Section 6 and conclude in Section 7.

2. Timeline

The U.S. is a major exporter and China is the largest importer of soybean, so it is the most relevant and influenced commodity in the trade war. Figure 1 shows the timeline of the events that took place from 2018 to 2020, and real futures prices of the five commodities during the same period.

In response to trade damage from continued tariff retaliation and trade disruptions, the USDA announced a trade aid package valued up to $12 billion on July 24, 2018, and a second one up to

$16 billion on May 23, 2019. Both packages included three components. First, the Market Facilitation Program (MFP) provided direct payments to farmers in proportion to actual harvested production in 2018 and planted area in 2019. Second, the Food Purchases and Distribution Program (FPDP) purchased commodities impacted by tariffs. Third, the Agricultural Trade Promotion (ATP) program helped finance foreign market development for affected agricultural products. Table 1 shows more details about these programs.

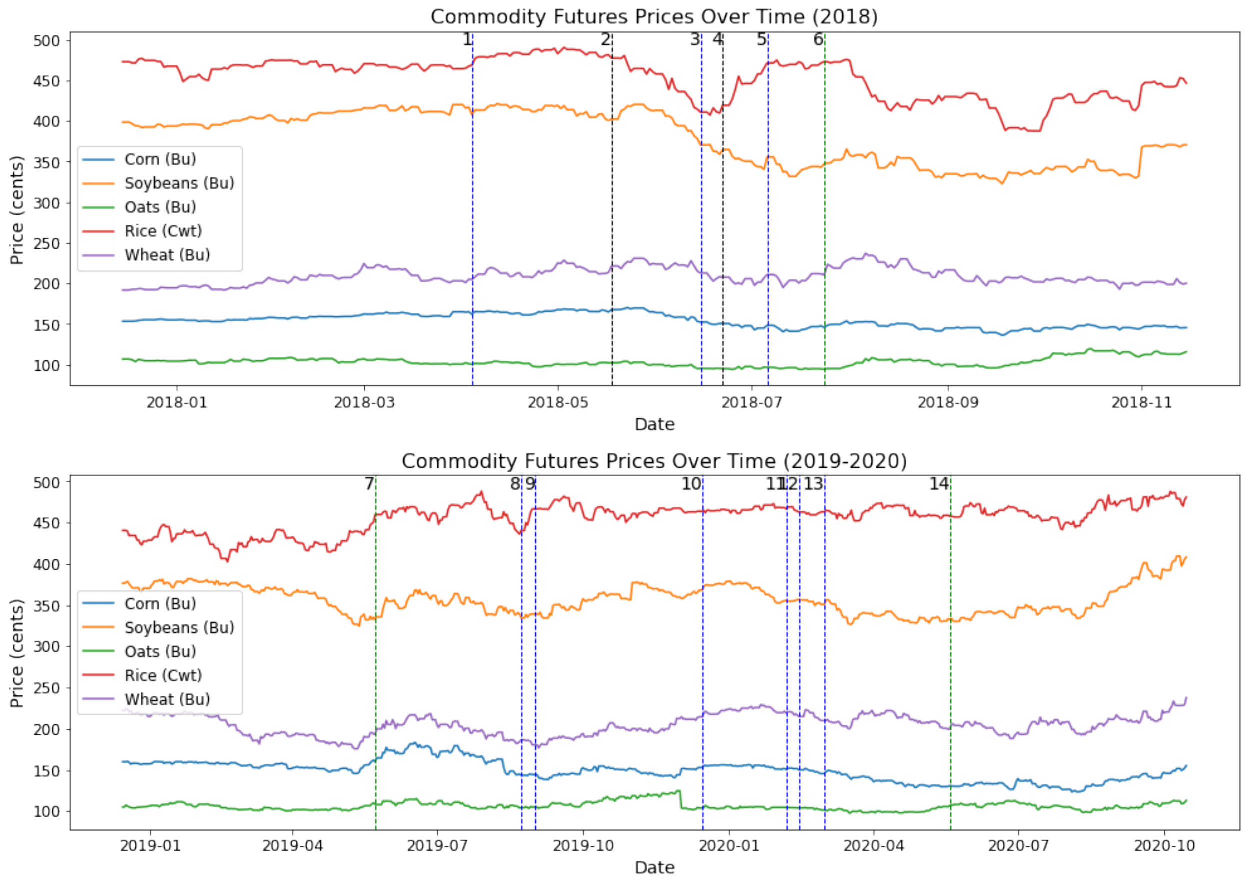

Figure 1 Timeline and Soybean Futures Price (1982-84 dollars)

Notes: From left to right, the vertical lines represent:
1. On 4/4/2018, China Responds to U.S. 301 Announcement.
2. On 5/18/2018, the EU announced a product list of additional tariffs.
3. On 6/15/2018, China Responds to U.S. 301 Announcement with Revised Product List.
4. On 6/22/2018, the first round of additional tariffs from the EU came into effect.
5. On 7/6/2018, the first round of additional tariff from China came into effect.
6. On 8/27/2018, 2018 Market Facilitation Program (MFP) first round was announced.
7. On 7/24/2018, 2018 trade aid package was announced.
8. On 5/23/2019, 2019 trade aid package was announced.
9. On 8/23/2019, China announced second round of additional tariffs.
10/11. On 9/1/2019 and 12/15/2019, the second round of additional tariffs from China was implemented.
12. On 2/6/2020, China announced that the tariff increase announced on 2019/8/23 would be decreased by one-half.
13. On 2/17/2020, China announced tariff exemption upon approvement.
14. On 5/19/2020, USDA announced it would provide additional direct assistance to farmers and ranchers impacted by the coronavirus through Coronavirus Food Assistance Program (CFAP).

Table 1 Release Dates and Values of USDA's 2018 and 2019 Trade Aid Packages

Program	2018		2019	
	Announcement Time	Total Value	Announcement Time	Total Value
Trade Aid Package:	July 24, 2018	up to $12 billion	May 23, 2019	up to $16 billion
MFP	First round: August 27, 2018 (50%) Second round: December 17, 2018 (50%)	Up to $10 billion	First round: July 25, 2019 (50%) Second round: November 15, 2019 (25%) Third round: February 3, 2020 (25%)	Up to $14.5 billion
FPDP		$1.2 billion		$1.4 billion
ATP	January 31, 2019	$0.2 million	July 19, 2019	$0.1 billion

Sources: For 2018, Congressional Research Service, "Farm Policy: USDA's 2018 Trade Aid Package", Jun 2019. For 2019, Congressional Research Service, "Farm Policy: USDA's 2019 Trade Aid Package", Nov 2019.

Soybean farmers benefited from the MFP and ATP since soybean did not appear on the purchased foods list by FPDP. MFP direct payments disbursed between 2018 and 2020 were as high as $23.14 billion, and accounted for over 80% of the total fund available for TAP, resulting in total subsidies to farmers increasing from just over $4 billion in 2017 to more than $20 billion in 2020. According to the USDA Economic Research Service (ERS), the amounts issued through MFP from 2018 to 2020 amounted to 6.40%, 17.96%, and 3.97% of total farm net income, respectively.

ATP, which only accounts for 1.67% and 0.63% of the aid packages in 2018 and 2019 respectively, are used by the two main FAS trade promotion programs: the Foreign Market Development Program (FMDP) and the Market Access Program (MAP). Though it is only a small proportion of the aid funds, it nearly doubled the combined funding for FMDP and MAP for 2018 and added almost 50% to their combined funding for 2019. According to the news on USDA Foreign Agriculture Service (FAS) in July 2019, U.S. exporters have had significant success since the $200 million was awarded, including a comprehensive marketing effort by the U.S. soybean industry that has increased exposure in more than 50 international markets. The reported benefit–cost ratio (BCR), the commonly used metric of the return on investment in export promotion, ranges from \$4 to \$60 per \$1 invested in export promotion, with an average of about \$10 (Williams, 2019). While the increased investment did not have the same high return as the initial funds due to diminishing marginal benefits, the return is still considerable.

3. Framework and Hypotheses

3.1. Spot Prices, Futures Prices, and Spreads

The model in this section largely follows Li and Chavas (2022). Consider an agricultural commodity that is priced in two markets in the United States, a futures market, and a spot market. Let S_t denote the spot market price at time t, $F_t^{(h)}$ the current nominal price of the futures contract that matures in h periods, and $\mathbb{E}_t[S_{t+h}]$ the expected future spot price at date $t+h$ conditional on the information available at t.

Consider an agent k who participates in the temporal arbitrage between spot markets at time t and at time $t+h$. She buys Q_{kt} amount of an agricultural commodity at price S_t at time t, stores the commodity for $h > 0$ periods, and sells it out at price S_{t+h} at time $t+h$. Let the cost of storage and transportation be $C_{kt}(|Q_{kt}|)$. By substituting τ by h, $P_{a,t}$ by S_t, $P_{b,t+\tau}$ by S_{t+h} into the Equation (A-1) in appendix A[3], we get the following condition when the optimal choice $Q_{kt} \neq 0$,

$$r^h \mathbb{E}_{kt}[S_{t+h}] - S_t = C'_{kt} + R'_{kt} \tag{1}$$

[3] τ, $P_{a,t}$ and $P_{b,t+\tau}$ are defined in Appendix A.

where $r \in (0,1)$ is a discount factor, C'_{kt} is the marginal transaction cost of storage and transportation, and R'_{kt} is the marginal risk premium. This formula follows Working (1949) and Wright and Williams (1982) aside from an expansion that captures the role of risk in arbitrage. Therefore, changes in the expectation of future spot prices, the marginal transaction cost, or the marginal risk premium will shift the demand curve for storage in the current period.

Consider another case where the agent k participates in speculation between the spot market and the futures market. The agent purchases a futures contract of Q_{kt}^{h} agricultural commodity with delivery h periods ahead at price $F_t^{(h)}$ at time t, and after getting the commodities at time $t + h$, she sells them out on the spot market at price S_{t+h}. Again, by Equation (A-1) in Appendix A, set $\tau = h$, $P_{a,t} = F_t^{(h)}$, and $P_{b,t+\tau} = S_{t+h}$, we have the following condition when the optimal choice $Q_{kt}^{h} \neq 0$,

$$r^h \mathbb{E}_{kt}[S_{t+h}] - F_t^{(h)} = C'_{kt} + R'_{kt} \tag{2}$$

where $r \in (0,1)$ is a discount factor, C'_{kt} is the marginal cost including margin deposit requirements and brokerage fees, and other related potential transaction costs such as transportation, and R'_{kt} is the marginal risk premium. Therefore, assuming that people have rational expectations, when $C'_{kt} + R'_{kt}$ remains constant in the short term, the futures price in the current period moves in the same direction and magnitude as the expectation of future spot price based on the information available.

3.2. Model

We take soybean as our analysis object in this section. Since the U.S. is a major soybean exporter, the supply is primarily the sum of domestic production and the inventory from previous periods in the first quarter of each marketing year (September to November each year), and in other quarters only consists of the storage from previous periods. According to USDA (2010), the planting season of U.S. soybeans is from late April to late June. However, China's retaliatory tariff increase on U.S. soybeans was officially announced on June 18, 2018, and came into effect on July 6, 2018, which was after the end of the planting season.[4] Because the planting area could not be changed for that season, the main production shifter was the weather shock in 2018. Since producers in the soybeans market can be viewed as price takers, we assume the spot market supply is competitive and upward sloping, determined by the marginal cost of storage and the weather shock. The marginal cost of storage consists of two parts, a physical cost, and an opportunity cost to hold rather than sell. The physical cost of storage includes the rent of storage bin, the expense to run the drying equipment, and cost in spoilage. And the opportunity cost depends on the normal rate of return on capital.

On the demand side, the U.S. soybean exports have steadily accounted for half of production value for several years since 2008 (Figure 2), so we model soybean market demand as the horizontal summation of the domestic demand, D_D, other countries' import demand for U.S. soybeans, D_X, and storage demand, D_I. We model each of these three demands by a downward sloping demand curve. We treat the demand as competitive for there are numerous domestic consumers, farmers that demand on-farm storage, commercial grain merchants that demand off-market storage, and many international trading companies that import soybeans in other countries.[5]

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[4] There was news that China was going to impose 25% tariffs on imports of 106 U.S. products including soybeans on April 4th, 2018, by Xinhuanet, an official Chinese media. However, the news was retrieved soon after. Bloomberg also reported the news but then retrieved it later.

[5] Compared with corn, wheat and rice, China's soybean imports are more open and market-oriented - not only state-owned enterprises but also many private enterprises are involved. In addition, the self-sufficiency of rice and wheat is an important policy of China, so the import volume of other staple grains except soybeans is relatively small.

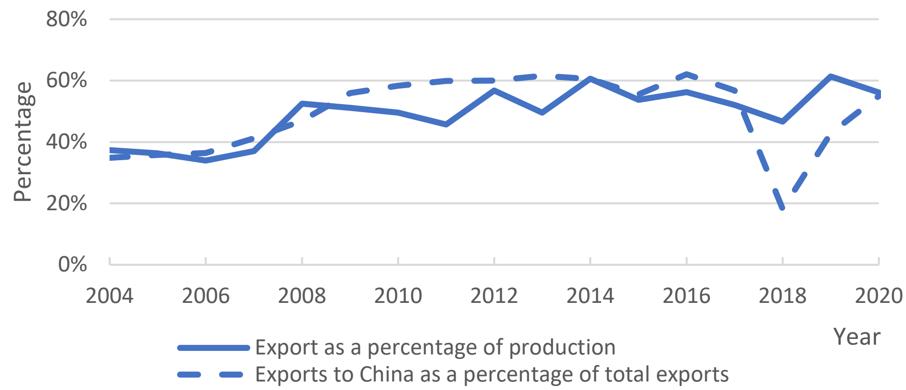

Figure 2 U.S. Soybean Production, Exports, and Exports to China, 2004-2020

Sources: USDA NASS and USA Trade Online

When the news about the retaliatory tariff was announced, the domestic demand and export demand did not shift immediately because the enforcement was designated to be several weeks later. However, the producers and the market expected the demand to drop once the tariff was in place, then the storage demand decreased since the expected price decreased according to Equation (1). Thus, as shown in Figure 3, the equilibrium point changed from point B to A, which led to a decrease both in price and quantity. Correspondingly, there was an increase in export quantity along the export demand curve from T_0 to T_1 due to the lower price, a drop in inventory from I_0 to I_1, and an increase in domestic demand along the curve as well. Our first hypothesis is that the spot price decreased from P_0 to P_1 when the retaliative tariff was announced, but not as much as when the change actually happened several weeks later.

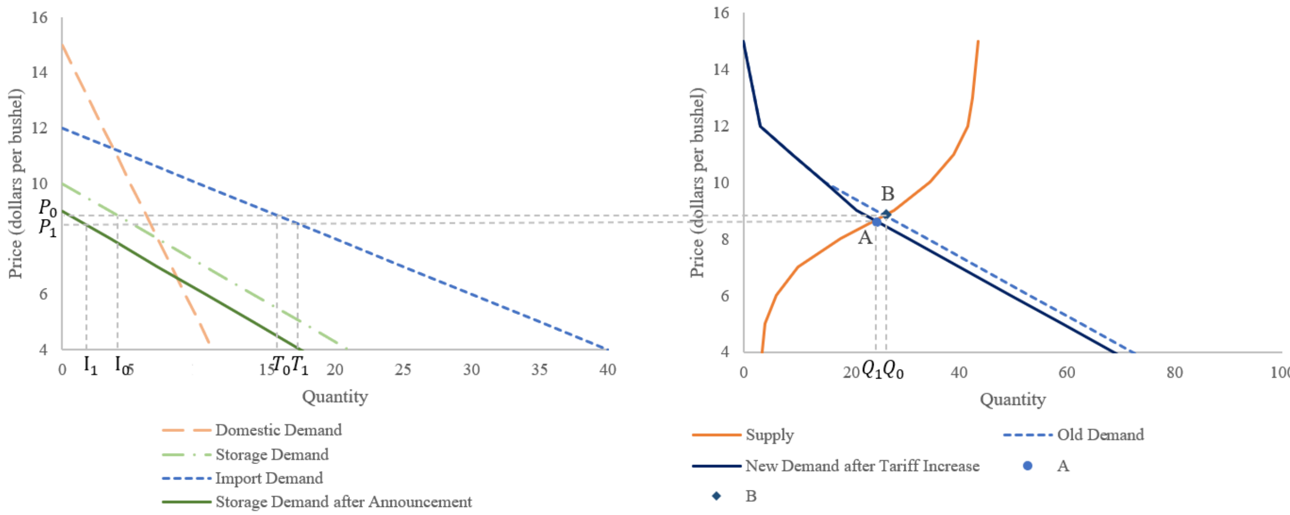

Figure 3 Schematic Figure of the Impact of Retaliatory Tariff Announcement

When the tariff was imposed on July 6th, 2018, the export demand shifted downward due to higher tariff cost, so in the right panel of Figure 4, the total demand curve shifted from the light blue dashed curve to the dark blue solid curve. In the long term, the U.S. farmers could resource their exports to other countries, though these countries may offer lower prices than Chinese firms, so the aggregate demand curve may partially rebound. Also, farmers will reduce the planting area in the next planting season due to the high inventory, so the expected supply curve for the next year will shift to the left. Therefore, the farmers would have reasonably expected the soybeans price to rebound in several months after the trade war was triggered. According to Adjemian et al. (2021), the effect on the spot price at the Gulf of Mexico lasted around five months, from June to November 2018. According to Equation (1), the storage demand was supposed to increase since the difference between expected price in the futures and current spot price became larger. However, the increase in storage demand cannot cover the total decrease in export demand. First, the proportion of soybeans that goes to storage is usually less than the amount that is traded. Soybeans spoil more easily than corn due to the high oil content and greater fragility during handling (Iowa State University Extension, 2008). Hence,the proportion of soybeans production to be stored is generally lower. Second, the storage was a challenge in itself with a record harvest in 2018. More soybeans were stored in 2018 than during the harvest months in previous years because it was a bumper year for soybeans. Thus, farmers might have to use older and smaller bins that are hard to clean out, with which came higher storage costs. Therefore, according to Figure 4, the equilibrium point moves from point D to C, which leads to a decrease both in price and quantity. There is a decline in total equilibrium quantity from Q_0 to Q_2, which breaks down to a decrease in export demand from T_0 to T_2, an increase in storage demand from I_0 to I_2, and an increase in domestic demand along the curves due to the lower price. We hypothesize that the spot price went down from P_0 to P_2 after the retaliatory tariffs came into effect. Another hypothesis following Equation (2) is that there was a drop in futures price of similar magnitude on the announcement of the retaliation.

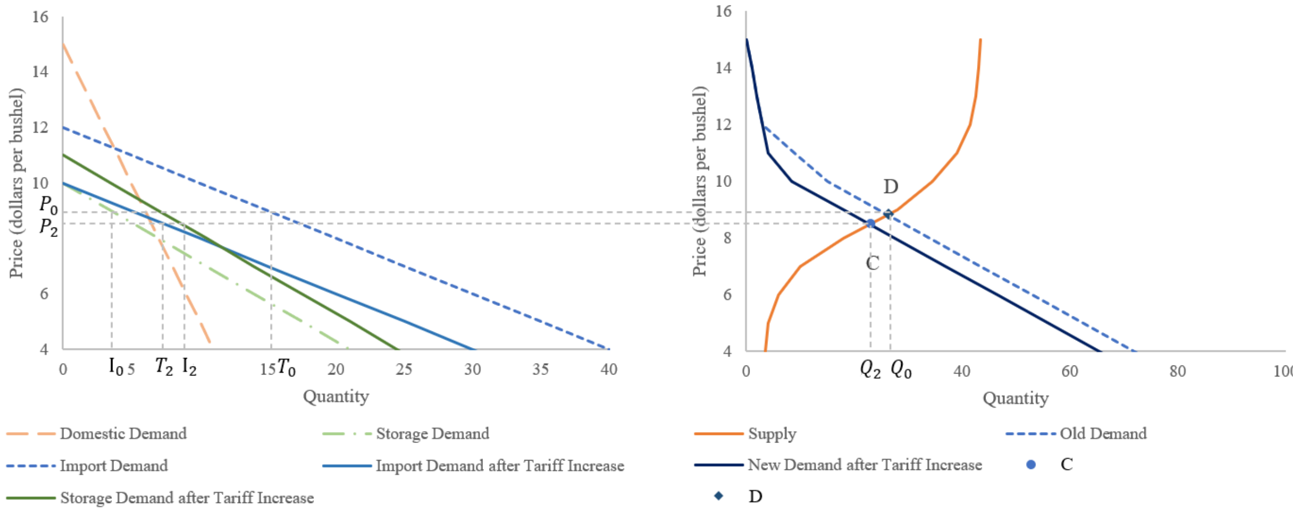

Figure 4 Schematic Figure of the Impact of Retaliatory Tariff Implementation

Following the derivation above, the spread between spot price and futures price should become more negative from the day of announcement to the day of implementation, and then the gap gradually decreases to normal level after several months. Moreover, by evaluating the effect on spreads of different length, we should be able to give some suggestive evidence on the farmers' expectation of the persistence of the trade war effect. The longer the spread length, the more negative the effect will be. The magnitude of the negative effect will not become larger, when the spread length gets longer than the expected duration of the effect.

As for the MFP direct payments, since they are designed to decouple with production, it should not change the dynamics on the supply side. Although they are lump sum payments and were not supposed to affect market demand, they might be viewed as a demand side shock. There are two possible channels that the payments can affect the inventory demand. From Equation (1), the spot price depends on cost of storage and risk premium keeping the expectation of future price unchanged. The direct payments to the farmers could have affected the cost of storage by supplementing the farmers' working capital, stabilizing their financial conditions, and reducing interest on capital borrowing (Swanson, Schnitkey, and Coppess, 2018). Alternatively, the payments might have reduced the marginal risk premium by reducing the variance in farmers' profits and raising farmers' income. As Figure 5 shows, the equilibrium point moves from point E to F, increasing both price and quantity. There are decreases in export quantity and domestic consumption along the curves due to the higher price, and an increase in storage quantity in equilibrium from I_2 to I_3. Following Equation (2), we thus hypothesize that the futures price rose from P_2 to P_3 when the TAP was announced.

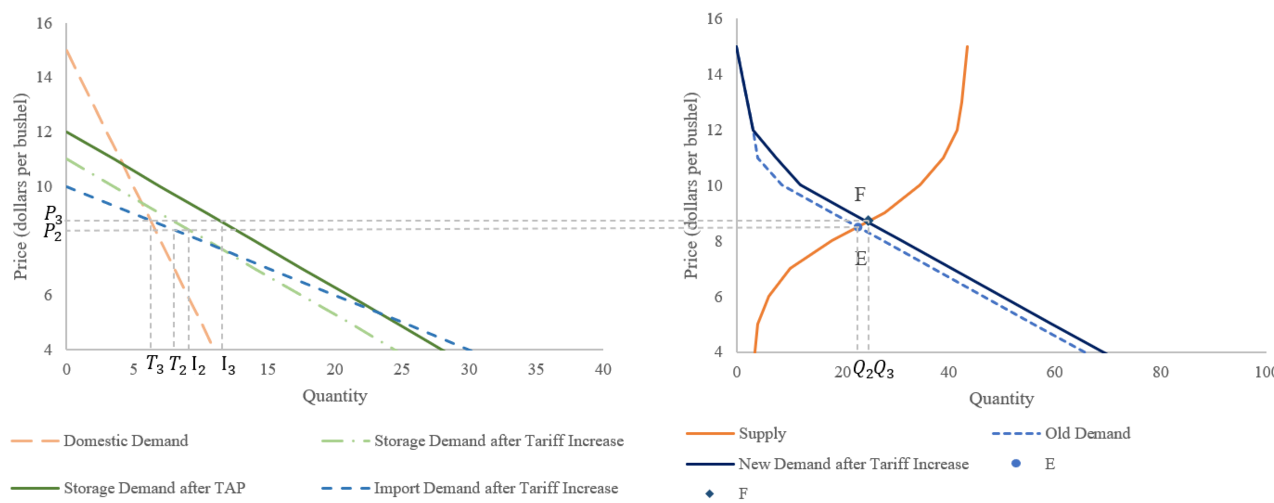

Figure 5 Schematic Figure of the Impact of MFP Payment

4. Data Description and Summary Statistics

4.1. Prices Data

Table 2 reports the summary statistics of U.S. soybean futures daily closing nominal prices of November contracts traded one year or less prior to delivery. We also show the real prices in 1982-

84 dollars deflated by the Consumer Price Index (CPI). The data spans 2004 to November 2020 and consists of 4,149 observations. It was downloaded from the Barchart website[6]. There were no large fluctuations in tariffs of soybean between the U.S. and its major trading partners from 2004 until early 2018 when the trade war was initiated. Over the period, the futures prices ranged from 509.50 to 1,768.25 in nominal dollars, and from 267.03 to 767.01 in real dollars. The peak occurred in 2012 and the trough in 2004. The futures spreads varied from –69.5 to 412 nominal dollars, and –31.80 to 179.19 in real dollars. The peak and trough occurred in 2012 and 2008, and in 2012 and 2006, respectively. Additionally, daily spot prices at sub county level are available on USDA Market Service Website[7], which can be used to construct spreads.

[6] Barchart Website. Available online: https://www.barchart.com/futures/grains.
[7] USDA Market Service Website. Available online: https://www.marketnews.usda.gov/mnp/ls-report-config?category=Grain.

Table 2 Summary Statistics of Soybean Nov. Contract Futures Prices (cents/Bushel)

	Nominal Price				Real Price (1982-84 dollars)			
year	Mean	StdDev	Min	Max	Mean	StdDev	Min	Max
2004	639.80	80.45	509.50	788.50	338.98	45.02	267.03	421.43
2005	616.64	52.64	520.75	765.75	315.82	27.60	270.66	395.33
2006	618.91	48.49	538.50	740.00	307.04	24.01	265.53	364.35
2007	878.88	97.80	712.75	1126.50	423.40	42.66	350.35	532.76
2008	1211.00	205.41	802.50	1631.00	562.09	92.79	379.62	744.69
2009	959.44	64.27	791.25	1089.75	447.00	28.42	372.36	507.36
2010	1020.35	114.05	894.25	1308.50	467.64	49.99	411.72	593.50
2011	1307.68	81.06	1119.50	1457.50	581.49	38.36	492.80	644.61
2012	1408.13	160.08	1170.00	1768.25	613.17	68.33	513.51	767.01
2013	1255.51	60.29	1135.00	1396.00	539.00	26.56	483.56	597.75
2014	1100.57	98.04	910.25	1270.75	464.95	41.86	383.30	536.37
2015	932.87	44.27	861.75	1037.25	393.62	19.70	362.85	438.24
2016	981.95	70.20	870.00	1162.75	409.04	28.08	365.56	484.19
2017	978.87	30.39	911.00	1043.25	399.36	12.58	373.09	426.99
2018	947.94	74.12	814.00	1053.50	377.62	31.07	322.68	421.47
2019	918.30	34.88	827.50	978.75	359.19	14.10	324.30	381.81
2020	918.31	65.29	839.00	1087.75	355.31	23.54	326.42	417.84

Source: Barchart Website. Available online: https://www.barchart.com/futures/grains

4.2. Tariff Data

We compiled a daily panel dataset of retaliatory tariffs on U.S. soybean exports from official documents published by the tax bureaus of Canada, China, Mexico, and the EU. We construct separate variables for the officially implemented tariff level, and the difference between the announced tariff level and the implemented tariff levels that formed people's expectation. We use Most Favored Nation (MFN) tariff rate data from the World Trade Organization (WTO) Tariff Download Facility (TDF) database. The export tariffs are aggregated to HS-6 level using the average export values over the past three years to the target country as weights. Figure 6 shows China's retaliatory tariff on soybean and the expected changes in tariff.

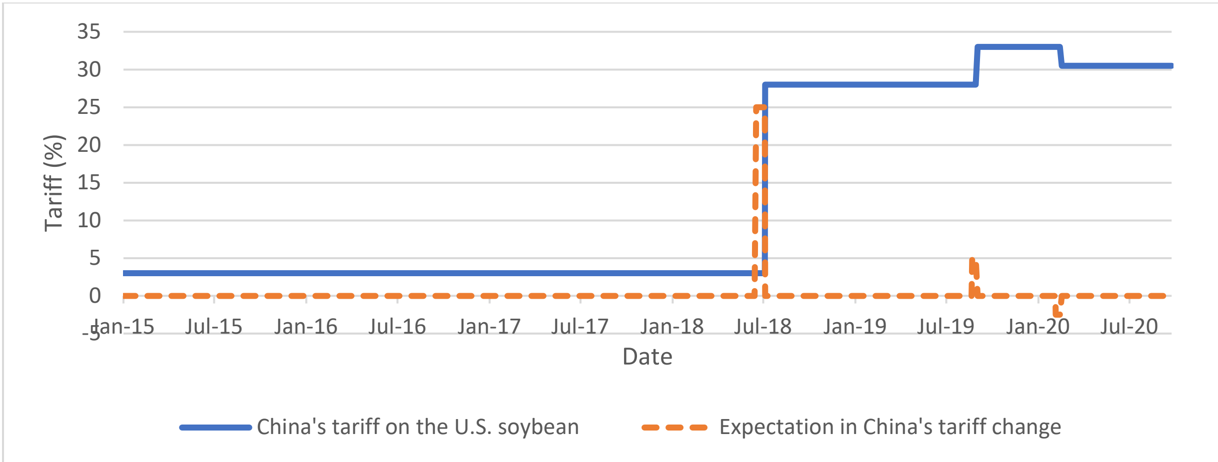

Figure 6 Timeline of Retaliatory Tariff on U.S. Soybean

Sources: WTO Tariff Download Facility database and the official website of the Ministry of Commerce of the People's Republic of China.

4.3. USDA World Agriculture Supply and Demand Estimation (WASDE) Reports

The WASDE is prepared and released by the World Agricultural Outlook Board (WAOB) monthly. It provides the current USDA forecasts of U.S. and world supply-use balances of major grains, soybeans and products, and cotton; and U.S. supply and use of sugar and livestock products. It is one of the important sources of information for participants in the futures market and affects market expectations. In this paper, we use the next marketing year's projection on the stocks, production, imports, and exports of both the U.S. and the major importers and exporters in the world. The descriptive statistics of the variables for soybeans from WASDA reports are shown in Table B-2 in Appendix B.

4.4. Weather Data

The primary source of weather data is Schlenker and Roberts (2009), which provides a mechanism to calculate detailed daily gridded weather dataset from 1981 to present with the station data. Grids are developed using Parameter-elevation Regressions on Independent Slopes Model (PRISM). PRISM interpolation routines simulate how weather and climate vary with elevation, and account for coastal effects, temperature inversions, and terrain barriers that can cause rain shadows. Station data are assimilated from many networks across the country.

We obtained the data on daily precipitation, and mean, minimum and maximum temperatures through Google Earth Engine, and averaged each variable by county. The country-level variables are then calculated as the weighted average across the fixed sample of counties, where the weight is acres planted of soybean in each county. The planting area data are obtained from NASS of the USDA.

The weather variables used here include growing degree-days (GDD) (8-30 °C), extreme degree-days (GDD) (>30 °C), and total precipitations during the growing season. The definition of the growing season follows USDA NASS (2010). Table 4 reports the summary statistics of these variables over the growing season.

Table 4 Summary Statistics of Weather Variables (Soybean)

	Mean	StdDev	Min	Max
Prcp.	765.06	2.69	760.83	768.48
GDD	2024.61	13.10	2005.23	2051.44
EDD	19.90	0.91	18.61	21.58

Notes: Prcp., GDD, and EDD are total precipitation, growing degree-days (8-30 °C), and extreme degree-days (>30 °C) during the growing season. They are calculated from the daily gridded PRISM dataset. We take the mean of temperatures and precipitations by county, and aggregate to country level using acres planted of each crop in the county as weights. The units are millimeters, degree-days and degree-days respectively. The summary statistics are calculated across the time span Jan. 2004 – Nov. 2020.

There can be some measurement errors in the weather data collection and aggregation which are uncorrelated with the true values. Thus, we expect that the weather coefficients will be biased towards zero.

5. Empirical Model and Estimation

5.1. Empirical Model

We use the following reduced-form regression design to examine how the tariff change influences the futures market outcomes.

$$y_t = \alpha + \tau_t\beta + D_t\delta + X_t\gamma + \omega_t + \eta_t + \varepsilon_t \tag{3}$$

where y_t is the outcome variable on date t, which is either real futures prices or spreads of soybean, corn, wheat, rice, or oats. τ_t consists of four variables, China's and EU's retaliatory tariffs imposed and the difference between the announcement and the implementation tariff levels that formed people's expectation.[8] The retaliatory tariffs imposed are the tariff rate that already came into effect, and the expectation terms represent the differences between the announced level and the actual level in implementation. Specifically, the expected difference variables are not 0 only during the period after the announcement but before implementation. The coefficient of the tariff expectation variable captures the effect of the news shock. D_t is a set of indicator variables for all types of financial aids to the farmers from 2018 to 2020 to deal with trade damages, the outbreak

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[8] We planned to use tariff variables for each major importing countries. However, since there is no variation in the soybean tariffs of the other three top importers, EU, Japan, and Mexico, we only have China's tariff on the U.S. soybean on the right-hand side of the model. The correlation coefficient between China's tariff on the U.S. soybean and the tariff change expectation is -0.11. There is no multicollinearity problem between these two variables. For the same reason, we only have China's and EU's retaliatory tariff variables on the U.S. corn, rice, and wheat, and China's tariff variables on the U.S. oats.

of the Coronavirus epidemic in 2020, and the payment to make up for pandemic losses, which are 1 after the events happened or the payment was announced, and 0 otherwise. X_t is the vector of control variables, including weather shocks, as well as the world and U.S. soybean supply and demand information from the USDA WASDE monthly reports[9]. ω_t is the year fixed effect and η_t is the month fixed effect, which capture the seasonality of the agricultural commodity market.

To identify the coefficients β, tariff changes must be uncorrelated with the unobserved supply and demand factors. We argue that the tariff changes are exogenous for the following reasons. First, these trade sanctions were enacted in retaliation for the tariff hikes initiated by the U.S., and the reasons for the U.S. tariff increases were to force China to reduce unfair trade practices and theft of U.S. intellectual property as claimed by the White House. The timing of the start of the trade war has nothing to do with the contemporary economic situation. So, we assert that the variations in tariffs are independent of relevant economic factors affecting soybean prices at or prior to the time of changes if the news were not leaked ahead of time. Second, the event studies and the preexisting trends checks in Fajgelbaum et al. (2020) and Carter and Steinbach (2020) show that prewar export trends are uncorrelated with retaliatory tariffs, and there was no evidence of an anticipation effect before the implementation of the tariff changes. Therefore, we treat the tariff variations as exogenous. Third, with the data from the WASDE reports by the USDA, some suspected omitted variables, such as projected import value of major importers and the export value from major exporters, are included in the regression, which also mitigates the concern with identification.

[9] The variables from WASDE reports include USDA's projections on the soybean stock, use, imports, exports, and production of the world's major importers, major exporters, and the U.S. in the following market year. Detailed data description is available in Table B-2 in Appendix B.

According to USDA (2010), the planting season of U.S. soybeans is between Early April and late June. However, China's retaliatory tariff increase on U.S. soybeans was announced on June 18, 2018, and August 23, 2019, with the official starting dates of July 6, 2018, and September 1, 2019, respectively, which were after the end of the planting season. Since the planting area cannot be changed then, the shifters of supply are mainly weather factors, which are exogenous. Thus, we control weather shocks in our regressions to reduce the variability in residuals.

The coronavirus pandemic might have made the entry review in other countries more cumbersome, but we have not seen any signs of a soybean embargo. On the contrary, in early 2020, the trade relation between the U.S. and China eased, and China promised to buy more U.S. soybeans, so exports resumed gradually in 2020. However, we still expect that the epidemic reduced domestic demand due to interrupted operations and production, which in turn led to a decline in futures prices. The impact on the spread depends on whether the market expected this disaster to end quickly. In response to the pandemic, the USDA announced details of direct assistance to farmers through the Coronavirus and Coronavirus Food Assistance Program (CFAP) on May 19, 2020, and its extension on September 17, 2020, which will provide up to $30 billion ($16 billion for CFAP1 and $14 billion for CFAP2) in total in direct payments to America's farmers and ranchers impacted by the coronavirus pandemic. The money will fill the working capital of the ranchers and support the restoration of livestock to pre-epidemic levels, thereby increasing the demand for soybean meal and soybeans. Thus, we expect that the CFAP funds will raise the soybean futures prices. Therefore, we include three Covid-19 related event dummies in our regression as control variables to reduce the variance of the residuals: the indicator of when 21 states implemented shelter-in-place order as a symbol of the outbreak, and two CFAP direct payments.

5.2. Non-Stationarity

A valid time series analysis requires stationarity and ergodicity of both the dependent variables and independent variables. We carry out both Augmented Dickey-Fuller (ADF) tests and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests to detect unit roots in the data generating process.[10] Table 5 shows the test results for each variable in the estimation equation.

The ADF test tests the null hypothesis that a unit root presents in a time series sample. If the p-value is greater than 0.05, we cannot reject the null that the series is not stationary. On the other hand, the KPSS test holds the null hypothesis that an observable time series is stationary around a deterministic trend (i.e., trend-stationary) against the alternative of a unit root. Hence, the variable is stationary if we reject the ADF test and fail to reject the KPSS test. Table 5 implies that there are unit root concerns with the soybean futures price of November contract, the imposed tariff rates by China, and the WASDE report variables. One possible method to fix the problem is to run the regression with the first differences of all the variables.

The positive serial correlation stems from the fact that there is only one harvest per year, but selling from stocks throughout the year. To solve the problem in inference, we take out first difference regression and use the Newey–West estimator for the covariance matrix of the parameters to draw robust conclusions to the t tests. We choose the maximum lag length to be the integer part of $1.3T^{\frac{1}{2}}$, which is 19 with 201 observations.

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[10] We carry out two different unit root tests for each variable since these tests can be sensitive and lead to unreasonable results sometimes.

Table 5 Results of Unit Root Tests (Soybeans)

variables	ADF statistics	ADF p-values	KPSS statistics	KPSS p-values
futures price, Nov contract	-2.4764	0.1213	0.7954	0.0100
planting season precipitation	-13.3901	0.0000	0.0265	0.1000
planting season mean temperature	-15.4426	0.0000	0.0211	0.1000
harvest season precipitation	-7.5278	0.0000	0.0135	0.1000
harvest season mean temperature	-7.6425	0.0000	0.0250	0.1000
growing degree days	-11.5867	0.0000	0.0203	0.1000
extreme degree days	-7.2312	0.0000	0.1503	0.1000
accumulated precipitation	-10.8351	0.0000	0.0840	0.1000
retaliatory tariff, China, imposed	-13.8884	0.0000	0.0476	0.1000
retaliatory tariff, China, expected	-2.5093	0.1132	1.4303	0.0100
beginning stocks proj., major exporter	-2.0899	0.2486	3.6529	0.0100
beginning stocks proj., major importer	-0.0754	0.9518	4.3044	0.0100
production proj., major exporter	-0.1890	0.9398	4.6652	0.0100
production proj., major importer	-0.4743	0.8969	0.9854	0.0100
imports proj., major importer	0.5683	0.9868	4.6629	0.0100
domestic crush proj., major exporter	-1.0295	0.7423	4.5619	0.0100
domestic crush proj., major importer	0.4652	0.9838	4.6490	0.0100
exports proj., major exporter	1.0495	0.9948	4.4654	0.0100
ending stocks proj., major exporter	-2.3785	0.1479	3.5415	0.0100
ending stocks proj., major importer	0.2665	0.9758	4.1940	0.0100
area planted	-1.7619	0.3995	2.9726	0.0100
area harvested	-1.7197	0.4210	3.0124	0.0100
yield per acre	-2.3926	0.1438	3.5072	0.0100
beginning stocks proj., U.S.	-2.3652	0.1518	1.0245	0.0100
production proj., U.S.	-1.7446	0.4083	3.6179	0.0100
imports proj., U.S.	-1.8834	0.3399	3.5366	0.0100
exports proj., U.S.	-0.7615	0.8302	4.2445	0.0100
ending stocks proj., U.S.	-2.7328	0.0685	1.4182	0.0100
average price proj., U.S.	-1.8886	0.3374	1.3356	0.0100

Note: For the KPSS tests, p-value is smaller than the indicated p-value if it is 0.0100, and p-value is greater than the indicated p-value if it is 0.1000.

6. Empirical Results

Table 6 reports the effects of the China's retaliatory tariff and USDA's direct assistance to farmers on the U.S. soybean real futures price. Column (1) reports the result of regressing the logarithm of the real futures price of November contract only on the total Chinese tariff applied, expected Chinese tariff change, and the implementation of additional tariff exclusion application. Columns (2)-(4) report the same regression with different sets of controls and fixed effects for time trend and seasonality. For columns (5)-(8), I take the first differences of all the variables in the equation and add in control variables and fixed effects sequentially.

As discussed above, we prefer the results in column (8). After taking care of the non-stationarity problem, the results are all significant and robust in magnitude as well. Column (8) shows that there was a larger effect on futures prices after the tariff change was announced than when it was implemented.[11] A 25% increase in tariff during the first round of retaliatory tariff holding projections and weather variables unchanged, decreased the futures real price by 25.5% at the time of the announcement. And it only caused a 17% of the 2018 average real price when the retaliatory tariff was in place. The effect was larger when the regulations were just announced. The price pass-through was quite large in the short term and the negative effects of retaliatory tariffs were mainly borne by the U.S. farmers.

[11] Due to the construction of the tariff variables, we can compare the effects of the announcement and the implementation of the tariffs by directly comparing the coefficients of Expected and Applied Tariff variables.

Table 6 Effects of Tariff Policies on U.S. Soybean Futures Price

	(1)	(2)	(3)	(4)
Dependent Var	Log(Soybean Futures Real Price)			
Total Chinese Tariff Applied	-0.0070***	-0.0071***	-0.0069*	-0.0026
	(0.0025)	(0.0010)	(0.0038)	(0.0031)
Expected Change in Chinese Tariff	-0.0115**	-0.0097***	-0.0130***	-0.0153***
	(0.0048)	(0.0016)	(0.0025)	(0.0025)
Chinese Additional Tariff Exemption	-0.0131	-0.0911***	-0.0009	-0.1345***
	(0.0226)	(0.0272)	(0.0461)	(0.0299)
Observations	201	201	201	201
Control Set 1	No	No	Yes	No
Control Set 2	No	No	No	Yes
Month FE and Year FE	No	Yes	Yes	Yes

	(5)	(6)	(7)	(8)
Dependent Var	First Difference of Log(Soybean Futures Real Price)			
Total Chinese Tariff Applied	-0.0068***	-0.0071***	-0.0073***	-0.0068***
	(0.0006)	(0.0011)	(0.0018)	(0.0015)
Expected Change in Chinese Tariff	-0.0065***	-0.0085***	-0.0072***	-0.0102***
	(0.0003)	(0.0009)	(0.0009)	(0.0014)
Chinese Additional Tariff Exemption	-0.1001***	-0.1525***	-0.0202	-0.1059***
	(0.0095)	(0.0321)	(0.1191)	(0.0375)
Observations	201	201	201	201
Control Set 1	No	No	Yes	No
Control Set 2	No	No	No	Yes
Month FE and Year FE	No	Yes	Yes	Yes

Notes: (1) * for $p<0.1$; ** for $p<0.05$; *** for $p<0.01$. The numbers in parentheses are Newey–West standard errors (max lag length is 19).

(2) The data period covers 2004 to Nov. 2020. Both Control Sets 1 and 2 include weather variables, such as accumulated precipitation, growing degree days, and extreme degree days, and WASDE report variables (For details on WASDE report control variables, please see Appendix A). Control Set 1 includes whole set of event indicators, including event dummies for the announcement of the trade aid packages in 2018 and 2019, the event dummy for when 21 states issued shelter-in-place orders, and the announcements of the Coronavirus Food Assistance Programs. Control Set 2 includes the actual payments to farmers through the MFP programs and CFAP programs instead of event dummies.

Despite the tariff exemption policies announced in 2020 for certain U.S. goods, the additional tariffs are still in effect. In 2020, China announced tariff exemptions for 696 U.S. goods, including soybeans and pork. These exemption policies were part of the Phase One Trade Agreement between China and the United States, aimed at boosting Chinese purchases of American goods and alleviating the tariff burden imposed during the trade war. These exemption policies allow Chinese enterprises to apply for tariff exemptions based on market conditions and commercial considerations, meaning that not all U.S. soybeans automatically qualify for exemptions. Based on the regression results, it can be inferred that the exemption policies introduced in March 2020 did not meet market expectations. Soybean farmers and traders were pessimistic about the Chinese market, and prices fell by 10.59% at the time the policy was implemented.

We then present the results for five main crops on the agricultural commodity markets, i.e., soybeans, corn, wheat, oats, and rice in Table 7. Table 7 implies that the China's tariff implementation also had significantly negative effects on wheat futures price, which was 12.75% upon announcement, about half the effects on soybeans. The effects of Chinese retaliatory tariffs on corn and rice were also negative but not significant. The additional tariffs EU imposed on the U.S. agricultural goods significantly affected corn by 14.5% when announced, but the effect faded away afterwards. Contrasted to other commodities, there is no effect of tariffs on oats prices, since the exports only accounted for less than 3% of the domestic production, and around 1% of the total supply in recent years. The U.S. is a major importer rather than exporter of oats, so the price of oats was unlikely to be affected by the retaliatory tariffs from China.

Based on Table 7, we can see that the effect of these payment programs on prices is very ambiguous, with both positive and negative impacts that are inconsistent. Even when significant, these effects are negligible. The phenomenon might be related to the timing of the announcement or payment. As is known well, farmers are most financially constrained during planting season rather than harvesting season. We plan to test the effect of MFP payments on inventory using detailed fund distribution data in future work.

Table 7 Effects of Tariff and Government Policies on Agricultural Commodity Futures

(First Differences)

	(1)	(2)	(3)	(4)	(5)
Dependent Var	Soy	Corn	Wheat	Oats	Rice
Total CHN Tariff Applied	-0.0068***	-0.0020	-0.0043***	0.0021	-0.0031
	(0.0015)	(0.0057)	(0.0014)	(0.0022)	(0.0067)
Expected CHN Tariff Change	-0.0102***	-0.0028	-0.0051***	0.0035	-0.0044
	(0.0014)	(0.0030)	(0.0013)	(0.0066)	(0.0034)
Chinese Tariff Exemption	-0.1059***	-0.1232***	-0.1377***	-0.0141	-0.0400**
	(0.0375)	(0.0383)	(0.0349)	(0.0299)	(0.0197)
Total EU Tariff Applied		-0.0072			0.0036
		(0.0058)			(0.0057)
Expected EU Tariff Change		-0.0058**			-0.0032
		(0.0029)			(0.0027)
MFP 2018	0.0000*	-0.0000	0.0000	-0.0000***	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MFP 2019	-0.0000**	-0.0000	0.0000	0.0000***	-0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CFAP	-0.0000*	0.0000	0.0000	0.0000**	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	201	201	201	201	202
Control Variables	Yes	Yes	Yes	Yes	Yes
Month FE and Year FE	Yes	Yes	Yes	Yes	Yes

Notes: (1) * for p<0.1; ** for p<0.05; *** for p<0.01. The numbers in parentheses are Newey–West standard errors (max lag length is 19).

(2) The data period covers 2004 to Nov. 2020. The dependent variable is the first difference of logarithm of the futures prices. All variables in the regression are in first differences. Control variables include weather variables, such as accumulated precipitation, growing degree days, and extreme degree days, and WASDE report variables (For details on WASDE report control variables, please see Appendix A).

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Appendix A. Derivation of the Relationships between Spot Prices, Futures Price, and Storage under Risk

Consider a representative market participant denoted by k. Suppose that she buys Q_{kt} of futures contract or commodity at price $P_{a,t}$ at time t, and sells the storage or delivery of commodity at price $P_{b,t+\tau}$ on the spot market at time $t+\tau$ $(\tau > 0)$.[12] Let $C_{kt}(|Q_{kt}|)$ be the transaction cost of Q_{kt} at time t, which includes the storage and transportation costs when the commodity is stored over time or transported over space, as well as the margin deposit requirements and brokerage fees if the transaction involves futures market. The present value of profit is then

$$\pi_{kt} = \left(r^{\tau} P_{b,t+\tau} - P_{a,t}\right) Q_{kt} - C_{kt}\,(|Q_{kt}|)$$

where $r \in (0,1)$ is a discount factor. Since the spot price $P_{b,t+\tau}$ is a random variable at time t, the market participant maximizes her expected utility,

$$\max_{Q_{kt}} \mathbb{E}_{kt}\left[U_k\left(\left(r^{\tau} P_{b,t+\tau} - P_{a,t}\right) Q_{kt} - C_{kt}\,(|Q_{kt}|)\right)\right]$$

where $\mathbb{E}_t[\cdot]$ is the expectation based on the information available to participant k at time t, and $U_k(\cdot)$ is a utility function representing the preference of participant k with $\frac{\partial U_k(\pi_{kt})}{\partial \pi_{kt}} > 0$ and $\frac{\partial^2 U_k(\pi_{kt})}{\partial \pi_{kt}^2} \leq 0$[13]. Assume both $U_k(\pi_{kt})$ and $\frac{\partial U_k(\pi_{kt})}{\partial \pi_{kt}}$ are continuous. When $Q_{kt} \neq 0$, the optimal decision is given by the first order condition:

$$\mathbb{E}_{kt}\left[U'_{kt} \cdot \left(r^{\tau} P_{b,t+\tau} - P_{a,t} - C'_{kt}\,\right)\right] = 0$$

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[12] In the situation where $Q_{kt} < 0$ or $Q_{kt}^{(h)} < 0$, it corresponds to market participant k selling $|Q_{kt}|$ or $|Q_{kt}^{(h)}|$.

[13] With risk aversion, $\frac{\partial^2 U_k(\pi_{kt})}{\partial \pi_{kt}^2} < 0$.

or

$$r^{\tau}\mathbb{E}_{kt}\left[P_{b,t+\tau}\right] - P_{a,t} = C'_{kt} + R'_{kt}$$

(A-1)

where $U'_{kt} = \frac{\partial U_k(\pi_{kt})}{\partial \pi_{kt}}$ is the marginal utility of agent k in time t, $C'_{kt} = \frac{\partial C_{kt}\,(|Q_{kt}|)}{\partial |Q_{kt}|}$ is the marginal transaction cost of buying or selling $|Q_{kt}|$, and $R'_{kt} = -\frac{r^{\tau}cov(U'_{kt}, P_{b,t+\tau})}{\mathbb{E}_{kt}[U'_{kt}]}$ is the marginal risk premium. The risk premium R_{kt} is the sure amount of money that satisfies

$$\mathbb{E}_{kt}[U_k(\pi_{kt})] = U_k(\mathbb{E}_{kt}[\pi_{kt}] - R_{kt}).$$

It presents the sure amount of money the decision maker is willing to pay to replace the random variable π_{kt} by its mean. And thus, the marginal risk premium R'_{kt} is the effect of buying Q_{kt} on R_{kt}.

Appendix B. Supplementary Tables

Table B-1 Tariff Schedule and Overview of U.S. Agricultural Products Exports

	China's tariff level before trade war (%)	China's applied tariff at the end of 2020 (%)	U.S. export / production (%) (2017)	Export to CHN / total export (%) (2017)	U.S. export / production (%) (2018)	Export to CHN / total export (%) (2018)
Corn (within quota)	1	31	19.30	1.59	24.77	0.46
Oats	2	7	11.08	12.85	5.83	2.66
Rice (within quota)	1	26	72.40	0.04	57.80	0.01
Soybeans	3	30.5	52.10	56.80	46.60	18.18
Wheat (within quota)	1	31	73.62	5.81	55.90	1.97

Sources: World Trade Organization (WTO Tariff Download Facility (TDF) database, U.S. Census Bureau, and USDA National Agricultural Statistics Service.

Table B-2 Summary Statistics of the WASDE Reports Variables

Country	Variable	Mean	StdDev	Min	Max	Count
Major importers	Beginning stocks	13.75	7.23	3.19	30.35	6149
	Production	17.60	2.02	14.50	21.83	
	Imports	86.81	26.90	50.54	134.29	
	Ending stocks	13.61	6.99	3.23	30.47	
Major exporters	Beginning stocks	42.49	10.48	24.94	62.57	
	Production	142.14	31.34	91.50	198.84	
	Exports	58.69	20.47	29.92	100.82	
	Ending stocks	44.41	9.68	22.94	63.97	
U.S.	Area planted	78.44	6.14	63.60	90.20	
	Area harvested	77.50	6.23	62.80	89.50	
	Yield per harvested acre	44.32	4.26	33.40	53.30	
	Beginning stocks	303.52	224.43	92.00	1070.00	
	Production	3454.83	577.43	2418.00	4693.00	
	Imports	15.45	9.36	3.00	65.00	
	Crushing	1792.85	169.21	1455.00	2180.00	
	Exports	1484.73	393.13	890.00	2290.00	
	Ending stocks	358.61	202.51	115.00	1045.00	
	Max average farm price	9.97	2.62	5.30	17.00	

Notes: Data in the table are projections in the soybean market of the next marketing year starting September.
Sources: USDA World Agricultural Supply and Demand Estimates Reports