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MFP and CFAP Official Announcement and Pre-official Announcement Effects on the Corn and Soybean Futures Market

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Abstract

This study examines the official announcement effect of the Market Facilitation Program (MFP) and the Coronavirus Food Assistance Program (CFAP) on the corn and soybean futures market. Using a permutation test and 2-stage GLS model, we find no significant official announcement effect. However, pre-official announcements significantly increase futures contracts' full-trading day volatility —by 0.945% (4 cents) for corn and 1.301% (16 cents) for soybeans. These findings suggest that information may have been absorbed by the market prior to the official announcements, indicating market efficiency. Moreover, the results highlight that pre-official announcements successfully serve as signals to boost market participants' confidence in the short-term following a negative market shock.

JEL Codes: Q02, Q13, Q18, G13

Keywords: official announcement effect, MFP, CFAP, corn, soybean, futures market efficiency, pre-official announcements

1. Introduction

In response to the U.S.-China trade war and the COVID-19 pandemic, the U.S. government, acting primarily through the Administration without a direct Congressional authorization or appropriation (Zulauf et al., 2020), implemented several rounds of ad hoc assistance programs. These included the Market Facilitation Program (MFP) and the Coronavirus Food Assistance Program (CFAP), which significantly increased payments to farmers. Corn and soybean producers were key beneficiaries of both MFP and CFAP payments. However, the effect of these program official announcements on the futures market remains unclear.

This study examines the effects of MFP and CFAP official announcements on corn and soybean futures, using absolute returns as a measure of volatility. To identify the official announcement effects, we use two methods. First, we use a permutation test to compare the absolute returns of corn and soybean futures on days when MFP and CFAP announcements were made to the returns in the other days in the event window, which consists of 5 days before and 5 days after the announcement. Second, we apply a two-stage Generalized Least Squares (GLS) model (Adjemian, 2012; Karali et al., 2010; Karali & Thurman, 2009) and find that the official announcement effects were insignificant. To explore the potential reasons for this, we examine several pre-official announcements that were released prior to the official program official announcements. We find that pre-official announcements can increase the full-trading day volatility. This suggests that by the time the official announcements were made, the market had already incorporated the information into futures, absorbing the official announcement effect (Pástor & Veronesi, 2012).

This study makes several contributions to the literature. First, it extends the research on government interventions in financial markets by examining how such programs can create uncertainty and volatility. Prior studies have focused on the impacts of government policies on bond and stock markets (Albulescu et al., 2021; Albulescu & Grecu, 2023; Amengual & Xiu, 2018; Kizys et al., 2021; Pástor & Veronesi, 2012). Our study extends to the corn and soybean futures markets, presenting empirical evidence that government programs such as MFP and CFAP—designed to mitigate the adverse effects of the trade war and the COVID-19 pandemic—had significant effect on these markets. Moreover, our study adds to the literature on market "signaling" through pre-official announcements. Previous studies have investigated pre-official announcement effects in various contexts, such as government spending shocks (Kriwoluzky, 2012), new product pre-official announcement signals (Prasad Mishra & Bhabra, 2001), and acquisition plan official announcement (Gao & Oler, 2012; Gokkaya et al., 2024), all of which use pre-official announcements as signals to gauge market reactions and allow for adjustments before making official announcements or plan. Our study shows that pre-official announcements of government programs work successfully as a signal to the market to boost market participants' confidence and expectations in the short-term following negative external shocks to the market. Finally, prior literature has extensively explored official announcement effects in various contexts—such as monetary policy and financial information on asset prices (Rigobon & Sack, 2004), stock markets (Christiansen & Ranaldo, 2007), and commodity prices (Scrimgeour, 2015), and the official announcement effect of information releases by USDA, such as the World Agricultural Supply and Demand Estimates (WASDE) and outlook information on commodity prices (Isengildina et al., 2008; Isengildina-Massa et al., 2008b, 2008a; Summer & Mueller, 1989). However, there remains a gap in understanding the official announcement effects of government ad hoc assistance programs in response to real-time events on commodity futures contracts. This paper, to our knowledge, is the first attempt to address this gap, offering insights that could be valuable for USDA policymakers.

This paper is structured as follows: Section 2 provides background information of MFP and CFAP. Section 3 reviews the related literature. Section 4 describes the information on data. Section 5 explains the methodology used in the analysis. Section 6 presents the results on the official announcement and pre-official announcement effects. Finally, Section 7 concludes with a summary of findings and policy implications.

2. Background

In response to economic damage caused by the U.S.-China trade conflict and the COVID-19 pandemic, the Congress passed new legislation and USDA created new ad hoc assistance programs, MFP and CFAP, to support U.S. producers (Janzen, et al., 2023). MFP and CFAP are two programs designed to provide financial aid to producers affected by market disruptions and trade disputes, with a specific focus on agricultural commodities such as corn and soybeans.

In 2018, the USDA introduced MFP to assist agricultural producers impacted by retaliatory tariffs imposed by several foreign governments. The MFP was first announced on August 27, 2018, and was implemented in two rounds—one in 2018 and another in 2019—comprising a total of five official announcements. The first official announcement in each year was about the payment structure and rate of payment by commodity, while the later official announcements were about the payment details. Approximately $8.6 billion was allocated for the first round of payments (Coppess et al., 2019; Giri et al., 2018; Janzen et al., 2023), and over two marketing years, around $23 billion was distributed to U.S. farmers (Janzen et al., 2023).

As an immediate response to COVID-19 pandemic's impact on U.S. producers, USDA in collaboration with the Small Business Administration (SBA) provided financial relief through the Coronavirus Aid, Relief, and Economic Security (CARES) Act. CFAP specifically supported producers who experienced a commodity price decline of five percent or more and/or incurred additional marketing costs. As the USDA's main COVID-19 relief program, CFAP was rolled out in two rounds. CFAP disbursed over $23.5 billion, constituting 51 percent of the total direct payments in 2020 (Giri et al., 2023). By March 2022, CFAP had provided $31.0 billion in direct payments to producers—$11.8 billion from CFAP 1 and $19.2 billion from CFAP 2 (Giri et al., 2022a; U.S. Department of Agriculture, Farm Service Agency, 2020a, 2020b).

There are two main reasons for focusing on the official announcement effects of MFP and CFAP on corn and soybean futures markets. The first reason is the substantial size of these payments compared to other government programs. Since their implementation, MFP and CFAP have become significant sources of direct government payments to the farm sector, with historically large payment amounts (Janzen et al., 2023). When MFP was introduced in 2018, it comprised over one-third of the total government payments in that year and rose to nearly two-thirds (63 percent) of total government payments in 2019. Similarly, in 2020, more than half of total government payments came from the USDA pandemic assistance program CFAP. By 2021, 29 percent of total government payments came from pandemic assistance programs, including CFAP. The size of the MFP payments in 2018 and 2019 represented a significant portion of farm income and exceeded payments made under Farm Bill commodity title programs (Coppess et al., 2019). From 2018 to 2020, rising farm incomes were in part driven by increasing government payments from MFP and CFAP. These programs accounted for 44%, 70%, and 77% of total government payments to farmers in 2018, 2019, and 2020, respectively. The combined CFAP payments were significantly larger than the total direct government payments in 2019, prior to the pandemic, and exceeded the average annual direct government payments over the previous 20 pre-pandemic years (Giri et al., 2022). The scale and reliance on these payments during this period mark an unprecedented development in U.S. farm policy history (Janzen et al., 2023).

The second reason is the unique authorization and specific contexts surrounding MFP and CFAP, which set them apart from other ad hoc assistance programs. Unlike typical farm payments, which require legislative oversight, MFP and CFAP were authorized under a unique authority granted to the USDA (Janzen et al., 2023). This allowed the USDA to bypass Congress and directly use the Commodity Credit Corporation (CCC), a government-backed financial entity capacity to borrow up to $30 billion, to fund these payments (Giri et al., 2023; Janzen et al., 2023; U.S. Department of Agriculture, Farm Service Agency, 2020a, 2020b). The discretionary use of the CCC linked these payments more directly to the Administration rather than Congress (Coppess et al., 2019; Janzen et al., 2023). Historically, ad hoc assistance payments have been provided to farmers as compensation for unforeseen negative events, such as natural disasters that disrupt agricultural production. In contrast, MFP and CFAP were specifically designed to offer immediate, real-time financial relief to producers impacted by trade disputes and the COVID-19 pandemic (Janzen et al., 2023).

Corn and soybean producers received payments under both rounds of the MFP and CFAP. While the MFP payments were aligned with U.S. farm policy by utilizing decoupled payments to avoid distorting planting and production decisions, Janzen, et al. (2023) provided empirical evidence that these payments increased on-farm inventories. This, in turn, affected commodity market prices. The MFP payments allowed producers to avoid selling at less favorable prices, which increased near-term prices while decreasing future prices. Such shifts in supply expectations could have resulted in heightened volatility in the commodity futures market. Building on this, we argue that the announcements of MFP and CFAP programs may have influenced agricultural producers' selling strategies, and thus, may have further been associated with an increased volatility in the futures market.

3. Literature Review

This study aims to understand whether official announcements of government programs can introduce extra volatility to the futures market. According to the efficient market hypothesis, futures prices typically experience increased volatility on official announcement days due to market participants adjusting their expectations in response to new information (Isengildina-Massa et al., 2008b; Summer & Mueller, 1989). In an efficient market, futures prices should reflect the expected return from holding a position rather than trading immediately based on spot prices. However, some studies argue that the official announcement of programs such as MFP and CFAP may not induce volatility if these events are anticipated, especially in countries with high levels of trust in government forecasts (Bomfim, 2003; Boulland & Dessaint, 2017; Engelhardt et al., 2021). This study investigates whether the official announcements of MFP and CFAP had an effect on the corn and soybean futures market.

Previous literature has extensively studied the effects of government interventions and policies on financial markets, particularly examining how these actions introduce uncertainty and volatility in stock and bond markets (Albulescu & Grecu, 2023; Pástor & Veronesi, 2012). A review of the impact of the COVID-19 pandemic shows that much attention has focused on the impact of government interventions on stock market returns and IPO returns (Albulescu, 2021; Alexakis et al., 2021; Baig et al., 2021; Goodell & Huynh, 2020; Zaremba et al., 2020, 2021) and bond markets

(Albulescu & Grecu, 2023; Pástor & Veronesi, 2012). Government intervention can significantly affect financial markets, though the direction of its impact often varies depending on the intervention's purpose. This study extends from existing literature by examining the announcement effects of MFP and CFAP on commodity futures markets, specifically focusing on corn and soybean futures prices and their absolute returns.

This study further contributes to the literature on official announcement effects. A large body of literature has focused on the impact of information released and official announcements made by USDA, such as forecast reports (Adjemian, 2012; Adjemian & Irwin, 2020; Dorfman & Karali, 2015; Garcia et al., 1997; Isengildina al., 2006; Isengildina-Massa et al., 2008a; McKenzie & Ke, 2022; Summer & Mueller, 1989). Using daily data, these studies examine the commodity return and volatility after the forecast report and news release. These studies generally find that the released news and forecast reports are followed by lower volatility in the futures commodity returns and that the commodity markets do respond to the released reports. Additionally, there is literature focusing on the official announcement effects of monetary policy on financial markets (Christiansen & Ranaldo, 2007; Rigobon & Sack, 2004). Typically, these official announcement effects arise due to information asymmetry, trader competition, and market expectations (Adjemian & Irwin, 2018).

While extensive literature exists on the impact of new information as well as new government programs, there is a gap when it comes to understanding the official announcement effects of a government financial support program on the futures contracts of commodities. Therefore, our study addresses this research gap. Given the USDA's efforts to manage the impact of its reports on commodity market volatility, we seek to determine whether the official announcements of government programs can affect corn and soybean futures.

Given the insignificant effect of program official announcements in our study, we reviewed prior research to better understand the reason. Previous studies suggest that pre-official announcements serve as signals, allowing firms to gauge market reactions and adjust their official plans. For example, Kriwoluzky (2012) found that a pre-announced fiscal policy shock—specifically, an anticipated increase in government spending—significantly decreases private consumption. Similarly, Prasad Mishra & Bhabra (2001) showed that product pre-official announcements positively impact stock prices only when they are credible and irreversible. Gokkaya et al. (2024) found that acquisition plan official announcements provide insights into future activity, reduce market uncertainty, and improve performance for firms announcing acquisitions from internal pipelines, benefiting from market feedback. Building on these studies, we examine whether pre-official announcements may have already shaped futures market participants' expectations before the official announcement release.

4. Data

Some interventions may create additional uncertainty (Pástor & Veronesi, 2012), while others, aimed at mitigating the negative effects of crises, such as trade tariffs or the COVID-19 pandemic, can reduce uncertainty (Albulescu et al., 2021; Amengual & Xiu, 2018; Kizys et al., 2021). In addition, economic support policies are shown to significantly stabilize fluctuations in bond prices (Pástor & Veronesi, 2012). MFP and CFAP fall into this latter category and are designed to provide financial support and alleviate financial strain that producers faced.

To analyze the official announcement effects of MFP and CFAP, we define "events" as the official announcement dates of MFP and CFAP, spanning from 2018 to the end of 2020. Each program having a total of five official announcements. Additionally, several pre-official announcements were made prior to the official release of each program round. The longest interval between a pre-official and official announcement is approximately two months for the first round of MFP, and around three weeks for CFAP. Pre-official announcements are defined as statements made by the U.S. Secretary of Agriculture, the President, or the USDA regarding financial relief programs before each official program announcement. Detailed schedules and information regarding these announcements are provided in Appendix Section 1 Table A1, which lists the specific dates of the official announcements.

We define the official announcement or pre-official announcement day as $k = 0$, and define a time index $k = -5, -4, -3, -2, -1, 0, +1, +2, +3, +4, +5$, representing the event window of 5 days before and 5 days after the official announcement or pre-official announcement day. Negative values of k indicate the days leading up to the event, while positive values capture the days following it. Thus, the event window for each official announcement or pre-official announcement is a total of 11 days (Isengildina-Massa et al., 2008a, 2008b; Summer & Mueller, 1989). To avoid overlap with other USDA announcements, such as the WASDE report, which may occur shortly before or after the official and pre-official announcements, we also construct a shorter event window of five days—spanning two days before and two days after the announcement day.

The primary variable of interest for examining the official announcement or pre-official announcement effect is the absolute return of futures prices, denoted as $ar_{i,t}$, calculated as follows:

$$
\begin{aligned}
ar_{i,t} &= \left|\ln\left(\frac{p_{i,t}}{p_{i,t-1}}\right)\right| * 100 \\
ar_{i,t}^{co} &= \left|\ln\left(\frac{p_{i,t}^{o}}{p_{i,t-1}^{c}}\right)\right| * 100 \\
ar_{i,t}^{cc} &= \left|\ln\left(\frac{p_{i,t}^{c}}{p_{i,t-1}^{c}}\right)\right| * 100 \qquad (1)
\end{aligned}
$$

where $p_{i,t}$ is the futures price for contract i (either corn or soybeans) on day t. For each trading day and each futures contract, we consider two types of prices: the opening price p^o and the closing price p^c. Specifically, $p_{i,t}^{o}$ is the opening price for contract i on day t, $p_{i,t-1}^{c}$ is the closing price for contract i on the previous day, $t-1$, and $p_{i,t}^{c}$ is the closing price for contract i on day t. Following previous literature Adjemian (2012), we use the absolute return of futures prices $ar_{i,t}$ as a measure of market volatility, where larger absolute price changes correspond to higher volatility. Since the precise timing during the day of official announcements and pre-official announcements is unknown, we calculate both close-to-open absolute returns, $ar_{i,t}^{co}$, capturing overnight volatility, and close-to-close absolute returns, $ar_{i,t}^{cc}$, capturing a whole-trading day volatility.

To calculate the absolute return, we collect daily trading data from Barchart, including traded volumes and opening and closing futures prices. The dataset only includes days when the market is open, excluding holidays and weekends. Our dataset includes 22 corn futures contracts, and 26 soybean futures contracts traded during the study period. To exclude contracts with low trading activity (e.g., those with only one or two trades during the study period), we limit the trading period to a maximum of 365 days, omitting contracts with more than 365 days to maturity. This results in a final sample of 20 corn futures contracts and 25 soybean futures contracts. The dataset starts on March 15, 2017, to capture the full trading history of each contract, accommodating the overlap of futures contracts—some approaching expiration as others begin trading (Karali & Thurman, 2009). On any given day, our dataset includes between one and five contracts for corn and between one and seven contracts for soybeans, reflecting the staggered trading schedule (Adjemian, 2012; Karali et al., 2010; Karali & Thurman, 2009). Contracts with varying times until maturity may respond differently to official announcements or pre-official announcements. To account for this, we calculate a variable called "time to delivery," defined as the number of days between the current date and the contract's maturity date. As suggested by previous literature (Adjemian, 2012; Arzandeh & Frank, 2019; Hu et al., 2020; Isengildina-Massa et al., 2008a; Peng et al., 2021; Wang & Chugh, 2014), the most actively traded contracts are typically those nearest to maturity. Therefore, we construct a dataset containing only the nearest-to-maturity contracts, with 8 contracts each for corn and soybeans.

Our analysis also includes commodity inventory levels and interest rates as additional variables. We incorporate inventory data from the quarterly Grain Stocks reports published by the National Agricultural Statistics Service (NASS) into our analysis. These reports provide inventory levels for corn and soybeans for specific survey dates in March, June, September, and December each year. Our focus is on corn and soybeans between 2018 and 2020, as this timeframe includes the MFP and CFAP official announcements. Since our other data are at a daily frequency, we employ interpolated splines to estimate daily inventory levels. The interest rate data are sourced from the Federal Reserve Bank of St. Louis and are available at a daily frequency.

5. Methodology

5.1. Statistical Tests

To assess the official announcement effect of government programs on corn and soybean markets, we use statistical tests to examine the these effects. Specifically, we compare the mean absolute returns on official announcement days with those observed in the five days before and after each official announcement or pre-official announcement. By analyzing whether there are significant differences in the mean absolute returns, we can determine whether the official announcements or pre-official announcements for MFP and CFAP have an effect on the futures market. Significant differences would suggest that these official announcements or pre-official announcements are associated with added volatility in the futures market.

Before proceeding to the statistical tests, we test the normality of the data to ensure the appropriate application of parametric or non-parametric tests. Descriptive statistics for corn and soybean futures contracts close-to-open and close-to-close returns, and their absolute values are presented in Tables 1. We conduct Jarque-Bera tests to test for normality and reject the null hypothesis.

[Table 1 inserted here]

Since the assumption of normality was rejected, non-parametric tests are preferred. Given that there are only 10 official announcements and 5 pre-official announcements, the maximum sample size for comparing absolute returns between the pre-official announcement or official announcement date and the surrounding days in the event window is 17. To address the small sample size, we apply a permutation test with 10,000 resamples. The permutation test generates a distribution of differences by repeatedly re-shuffling the data and introducing random signs under the null hypothesis that any observed difference is due to random variation. By comparing the observed difference to this distribution, we determine whether the difference is statistically significant. The permutation test is chosen over other non-paired non-parametric tests to ensure that comparisons are made within the same contracts and time periods.

5.2 2-Stage GLS

In addition to the permutation test, we estimate the official announcement and pre-official announcement effects of MFP and CFAP on the futures markets. The dependent variable is the absolute return $ar_{i,t}$, which serves as a measure of volatility. Both the absolute close-to-open return ($ar_{i,t}^{co}$) and the close-to-close return ($ar_{i,t}^{cc}$) are analyzed as separate dependent variables. We define a set of dummy variables $D_{k,t}$, for each day within the event window k = -5,…5, where $D_{k,t} = 1$ if day t falls exactly k days relative to an official announcement or pre-official announcement date, and $D_{k,t} = 0$ otherwise. Specifically, $D_{0,t} = 1$ if day t is the official announcement or pre-official announcement date; $D_{-5,t}$ to $D_{-1,t} = 1$ if day t is 5 to 1 days prior to the official announcement or pre-official announcement; and $D_{1,t}$ to $D_{5,t} = 1$ if day t is 1 to 5 days after the announcement or pre-announcement date. Additionally, we include control variables crop inventory $Inventory$, daily interest rates $Interest$ and time to delivery $TimeToDelivery$. The error term $\mathrm{E}_{i,t}$captures all unobserved factors affecting returns that are not explained by the included variables. We estimate the following equation:

$$ar_{i,t} = \theta_0 + \sum_{k=-5}^{5} \beta_k D_{k,t} + \theta_1 Inventory_t + \theta_2 Interest_t + \theta_3 TimeToDelivery_t + \mathrm{E}_{i,t} \quad (2)$$

However, using pooled OLS can lead to inefficiency due to two main issues—serial correlation and contemporaneous correlation. First, within the same contract, futures prices—and consequently absolute returns and residuals—are serially correlated over the trading period. That is, $\mathrm{E}_{i,t}$ is correlated with $\mathrm{E}_{i,t-1}$. Second, price movements of futures contracts with different delivery dates may be correlated on the same trading day due to shared exposure to underlying factors such as major news events (Adjemian, 2012; Karali et al., 2010; Karali & Thurman, 2009). Due to both serial and contemporaneous correlation in the error term, estimating Equation (1) using pooled OLS results in inefficient parameter estimates.

To address the inefficiency, we use the 2-stage GLS method to estimate equation (2) (Adjemian, 2012). In the first stage, we apply the Prais-Winsten GLS transformation (Winsten & Prais, 1954), , which adjusts for serial correlation within each futures contract. Specifically, for each contract i, we estimate its own first-order autocorrelation parameter, denoted as π_i. The Prais-Winsten transformation then corrects for serial correlation by subtracting π_i times the lagged value of each variable from its current value. This transformation is applied to both the dependent variable and the regressors, removing serial dependence in the residuals. To ensure that the transformed data exhibit residuals that are approximately independent and homoscedastic over time within each contract, we apply the Durbin–Watson test and report the results in Appendix Section 2.

However, after the first-stage transformation, residuals remain correlated across contracts traded on the same day. To address these contemporaneous correlations, we follow the approach of Karali and Thurman's approach and apply a second-stage GLS estimation to the transformed data from the first stage, as specified in Equation (2) (Adjemian, 2012; Karali & Thurman, 2009). In this stage, we specifically target to remove contemporaneous correlation among contracts traded on the same day, which can vary depending on how far apart the contracts are in terms of time to maturity. To quantify this distance, we rank all contracts traded on a given day by their days to maturity, assigning rank 1 to the contract with the shortest time to maturity.

To be clearer, Figure 1 illustrates the durations of multiple futures contracts, showing how these durations can be overlapped with each other, indicating several contracts can be actively traded on the same day. Within a single trading day, we define the futures contract position apart as the difference in ranks between two contracts. For instance, the first and second nearest-to-maturity contracts are one position apart, the first and third are two positions apart, and so forth. If only one contract is traded on a given day, the futures contract position apart is defined as zero.

In our dataset, the maximum number of corn futures contracts traded on the same day is five, while for soybeans it is seven. Therefore, to fully account for contemporaneous correlation, we control for correlations across contracts that are zero to four positions apart for corn and zero to six positions apart for soybeans. As a result, we construct a 5×5 correlation matrix $\widehat{\mathrm{P}^c}$ for corn and a 7×7 correlation matrix $\widehat{\mathrm{P}^s}$ for soybeans. Our goal is to remove these contemporaneous correlations.

Following Karali & Thurman (2009) and using the estimated correlation matrices $\widehat{\mathrm{P}^c}$ and $\widehat{\mathrm{P}^s}$, we construct the corresponding variance-covariance matrices for corn ($\widehat{\Sigma^c}$) and soybeans ($\widehat{\Sigma^s}$). We then apply GLS estimation to Equation (2) using these modified variance-covariance matrices. Assuming covariance stationarity over time and that contracts with similar time-to-delivery share the same covariance structure, this approach allows us to address both serial and contemporaneous correlation. As a result, the residuals are expected to be homoscedastic and independent.

[Figure 1 inserted here]

To estimate the correlation matrices $\widehat{\mathrm{P}^c}$ and $\widehat{\mathrm{P}^s}$, we follow a multi-step process. We begin by obtaining the residuals from the first-stage Prais-Winsten estimation for each contract. These residuals are corrected for serial correlation but may still exhibit contemporaneous correlation across contracts traded on the same day.

Next, we define residual vectors $e_{m,n}$ to isolate correlations between overlapping contracts. Specifically, we rank all futures contracts in the dataset by their maturity. For corn, there are 20 contracts ranked from 1 to 20; for soybeans, 25 contracts ranked from 1 to 25. We then identify the subset of trading days where two contracts (e.g., contract m and contract n) are both actively traded. The residual vector $e_{m,n}$ includes the residuals from contract m on the days that contract n is also traded. Conversely, $e_{n,m}$ contains the residuals from contract n on the same overlapping days. Figure 2 provides an example of $e_{m,n}$ and $e_{n,m}$ where $m = 1$ and $n = 4$. $e_{1,4}$ represents the residuals of the 1st contract on days when the 4th contract was also traded. Meanwhile, $e_{4,1}$ contains the residuals of the 4th contract on days shared with the 1st contract.

Once all residual vectors for overlapping contracts are defined, we group them by their futures contract position gap—i.e., how far apart they are in the maturity ranking. For example, all corn residual vectors with a 3-position gap, such as $e_{1,4}$, $e_{2,5}$, ……, $e_{17,20}$ are grouped together as $\begin{bmatrix} e_{1,4} \\ e_{2,5} \\ \vdots \\ e_{17,20} \end{bmatrix}$. According to this, we group another reverse set as $\begin{bmatrix} e_{4,1} \\ e_{5,2} \\ \vdots \\ e_{20,17} \end{bmatrix}$. These paired vectors are used in the system of equations (3) to estimate forward (ζ_3^f) and backward regression coefficients (ζ_3^b). The estimated correlation $\widehat{\rho_3}$ between corn futures contracts that are three positions apart is then calculated in equation (4).

Given that up to five corn contracts can be traded on the same day, we compute correlations from $\widehat{\rho_0^c}$ to $\widehat{\rho_4^c}$. Here, $\widehat{\rho_0^c}$ is the correlation of a corn contract with itself. Similarly, for soybeans, we compute correlations from $\widehat{\rho_0^s}$ to $\widehat{\rho_6^s}$. With these calculations, we can derive the correlation matrix $\widehat{\mathrm{P}^c}$ and the variance-covariance matrix $\widehat{\Sigma^c}$ for corn, as well as the correlation matrix $\widehat{\mathrm{P}^s}$ and the variance-covariance matrix $\widehat{\Sigma^s}$ for soybeans.

$$\begin{bmatrix} e_{1,4} \\ e_{2,5} \\ \vdots \\ e_{17,20} \end{bmatrix} = \zeta_3^f \begin{bmatrix} e_{4,1} \\ e_{5,2} \\ \vdots \\ e_{20,17} \end{bmatrix} + \begin{bmatrix} v_{1,4} \\ v_{2,5} \\ \vdots \\ v_{17,20} \end{bmatrix},$$

$$\begin{bmatrix} e_{4,1} \\ e_{5,2} \\ \vdots \\ e_{20,17} \end{bmatrix} = \zeta_3^b \begin{bmatrix} e_{1,4} \\ e_{2,5} \\ \vdots \\ e_{17,20} \end{bmatrix} + \begin{bmatrix} v_{1,4} \\ v_{2,5} \\ \vdots \\ v_{17,20} \end{bmatrix} \tag{3}$$

$$\hat{\rho} = \sqrt{\widehat{\zeta^f}\widehat{\zeta^b}} \tag{4}$$

[Figure 2 inserted here]

As a robustness check beyond the 11-day event window, we also examine the impact of official and pre-official announcements on the most actively traded contracts. Specifically, we use a dataset that includes only the nearest-to-maturity contracts and apply the estimation. The results are reported in Table A3 (Appendix Section 3). In this case, since only one nearest-to-maturity contract is traded per day—eliminating contemporaneous correlation, there is no need to apply 2-Stage GLS estimation. Additionally, to avoid potential bias from overlapping USDA announcements, we conduct another robustness check using a shorter 5-day event window—spanning two days before and two days after each event. We apply the same two-stage GLS estimation to this window, and the results are presented in Table A4a and Table A4b (Appendix Section 4).

6. Results

6.1. Results from Permutation Tests

We begin by examining the official announcement effect using permutation tests with 10,000 resamples. As shown in Table 2, the test statistics range from -0.69 to 1.17 and are not significant, indicating that for both corn and soybean futures, we fail to reject the null hypothesis of no significant difference in absolute returns on the official announcement day compared to the other 10 days in the event window. This suggests that there is no significant official announcement effect of MFP and CFAP on corn and soybean futures absolute returns. These results imply that the official announcements may have aligned with market expectations, with the information that was likely to be already incorporated into the futures contracts.

To investigate the absence of a significant official announcement effect, we examine whether pre-official announcements—issued ahead of the official program announcements—had a measurable impact. As shown in Table 2, the test statistics for absolute close-to-open returns for both corn and soybean futures contracts are not significant. However, when using absolute close-to-close returns, we find a significant pre-official announcement effect at the 1% level. To validate these findings, we also apply a two-stage GLS estimation.

[Table 2 inserted here]

6.2.Results from 2-Stage GLS

The two-stage Generalized Least Squares (GLS) estimation to is applied to further examine the potential official announcement or pre-official announcement effects on corn and soybean futures contracts, as outlined in Equation (2). The results, presented in Table 3, analyze the official announcement effects on both corn and soybean futures, using absolute close-to-open and absolute close-to-close returns as dependent variables. The coefficients for the official announcement dummy variable are not statistically significant in any of the cases, indicating no significant official announcement effect. These findings align with the results from the permutation test presented in Table 3, confirming the conclusion of an insignificant official announcement effect.

[Table 3 inserted here]

Turning to the pre-official announcement effect, Table 4 shows that pre-official announcements lead to a statistically significant increase in absolute close-to-close returns, but not in absolute close-to-open returns. The effect is significant at the 5% level for corn and the 1% level for soybeans. Several factors may explain this pattern. First, the market may require time to fully incorporate new information into futures prices. Since close-to-close returns capture the entire trading day volatility, whereas close-to-open returns reflect only overnight volatility, full-trading day volatility is better at capturing the market's full response to pre-official announcements. Another possible explanation relates to the timing of these announcements. While the exact announcement timing is unknown, it is highly likely that many of these pre-official announcements occurred during trading hours, especially between 8:30 AM and 1:20 PM Central Time, which would affect the full-trading day volatility but not overnight volatility. Still, the significant pre-official announcement effect and the insignificant official announcement effect, suggests the efficiency of the corn and soybeans futures market—the market reacts and absorbs new information.

The impact of pre-official announcements on full-trading day volatility for corn and soybean futures is 0.945% for corn and 1.301% for soybeans. With an average corn price of $4.25 per bushel and a contract size of 5,000 bushels in the study period, this translates to a price shift of $201 per corn futures contract, or 4 cents per bushel. Similarly, for soybean futures, pre-official announcements result in a 1.301% increase in one-day close-to-close absolute return. With an average soybean price of $10.73 per bushel and a contract size of 5,000 bushels, this leads to a price shift of $698 per soybean futures contract, or approximately 14 cents per bushel for soybeans. These magnitudes are nontrivial, especially for commercial producers and traders managing large positions. Moreover, the observed volatility and market response to pre-announcements reflect shifting expectations regarding government support. As noted by Janzen et al., (2023), such programs can "buy time" for producers, allowing them to delay marketing decisions rather than selling at less favorable prices. Our results provide empirical evidence of market participants adjusting their trading strategies in response to anticipated policy intervention.

Our results then indicate that pre-official announcements serve as successful signals for market participants by changing their expectations. By the time the official announcements are made, much of the relevant information has already been incorporated into futures prices, thereby reducing the effect of the official announcements themselves. Compared to official announcements, pre-official announcements work more as policy signals. When policymakers observe deteriorating market conditions—often triggered by negative shocks such as rising tariff rates—they may issue pre-announcements to reassure the market. These signals are intended to boost market confidence and communicate that the government is prepared to intervene to stabilize the situation. Importantly, pre-official announcements do not need to contain detailed policy measures.

Instead, their primary role may be to reduce uncertainty and anchor expectations. These results then reinforce the importance of strategic communication: pre-announcements serve not only as informational signals but also as tools to stabilize expectations and manage volatility. Clear, timely pre-announcements may help reduce uncertainty and mitigate sharp market swings, especially in periods of heightened risk.

As noted in the corporate finance (Gao & Oler, 2012; Gokkaya et al., 2024; Kriwoluzky, 2012; Prasad Mishra & Bhabra, 2001), firms often pre-announce acquisitions or product launches to gauge market reactions and guide future actions. Similarly, pre-official announcements may serve as a form of forward guidance, allowing market participants to update their expectations regarding the likely direction, timing, and scale of forthcoming interventions. Policymakers can also use market feedback to refine their strategy. These can also help explain the insignificant effect of official announcements, as the information may no longer come as a surprise to the market.

[Table 4 inserted here]

As a robustness check, we present results for the nearest-to-maturity contracts in Table A3 and for a shortened 5-day event window in Tables A4a and A4b. Since the number of pre-official announcements is smaller than that of official announcements and only eight futures contracts are available for both corn and soybeans, there is limited variation for estimating the pre-official announcement effect on volatility for nearest-to-maturity contracts. Despite this limitation, the overall findings remain consistent with those reported in Tables 4 and 5. We continue to find a significant pre-official announcement effect on full-trading day volatility for both corn and soybean futures.

7. Conclusion

This study provides a comprehensive analysis of the official announcement and pre-official announcement effects of government financial support programs, such as MFP and CFAP, on corn and soybean futures contracts. To study the official announcement and pre-official announcement effect, this study uses permutation test and 2-stage GLS model (Adjemian, 2012; Karali et al., 2010; Karali & Thurman, 2009). In conclusion, we find that while official program official announcements do not significantly impact the futures market, pre-official announcements do influence corn and soybean futures full-trading day volatility. Specifically, pre-official announcements lead to average absolute return increases of 0.945% in corn futures contracts and 1.301% in soybean futures contracts.

These results indicate that pre-official announcements can serve as effective signals to restore market confidence in the wake of negative market shocks. Our study expands the existing literature on the effects of government interventions by extending the analysis from bond, stock, and equity markets to the commodity futures markets. By focusing on these commodities, we provide new evidence on how ad hoc assistance programs, such as the MFP and CFAP, influence futures markets. Moreover, this research contributes to the growing body of literature on official announcement effects by exploring the impact of these programs on futures contracts in agricultural markets.

USDA data indicate that during the study period, net farm income and net cash income for producers increased significantly, largely due to substantial government payments. However, due to data limitations and the extended disbursement windows of the MFP and CFAP programs, our study could not precisely assess how these payments alleviated producers' financial challenges. Additionally, the exact timing of both official and pre-official announcements is unclear. These limitations highlight an opportunity for future research to investigate the direct impact of these payments on producers' financial outcomes and to examine the announcement effects within days of the events.

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Tables and Figures

Table 1: Descriptive statistics for futures return

Corn	Mean	Median	Variance	Count
		Corn		
Close-to-open return	-0.049	-0.060	0.207	16,324
Absolute close-to-open return	0.281	0.179	0.130	16,324
Close-to-close return	0.022	0	1.07	16,324
Absolute close-to-close return	0.680	0.448	0.612	16,324
		Soybeans		
Close-to-open return	0.013	0	0.272	19,385
Absolute close-to-open return	0.340	0.203	0.156	19.385
Close-to-close return	0.032	0.027	0.841	19,385
Absolute close-to-close return	0.634	0.453	0.440	19,385

Table 2 presents mean, median, variance, and number of observations for corn and soybean futures returns for all contracts that have traded volume greater than 0 during the study time.

Table 2: Results for Permutation Test on Official announcement Effect

Tests	Absolute close-to-open return	Absolute close-to-close return
Official Announcement Effect		
Corn	1.17	1.17
Soybean	-0.69	-0.69
Pre-official Announcement Effect		
Corn	1.20	2.41***
Soybean	1.15	2.19**

*p<0.1; **p<0.05; ***p<0.01

Table 2 presents the test statistic of the permutation test with 10,000 resamples. Insignificant test statistics suggest that the observed differences in absolute returns on the official announcement day and pre-official announcement days compared to the days before and after the official announcement and pre-official announcement are attributable to random variation, indicating no significant official announcement effect or pre-official announcement effect.

Table 3: Results for the Government Program Official announcement Effect on Absolute Commodity Returns

	Corn		Soybeans	
	Absolute close-to-open return	Absolute close-to-close return	Absolute close-to-open return	Absolute close-to-close return
5 days before	-0.065 (0.167)	-0.142 (0.399)	-0.087 (0.141)	-0.751 (0.448)
4 days before	-0.049 (0.167)	-0.087 (0.399)	-0.010 (0.141)	-0.162 (0.448)
3 days before	-0.034 (0.167)	0.129 (0.399)	-0.000 (0.141)	0.764 (0.448)
2 days before	-0.094 (0.167)	0.729* (0.399)	-0.074 (0.141)	0.868* (0.448)
1 day before	-0.063 (0.167)	-0.312 (0.399)	-0.012 (0.141)	-0.720 (0.448)
Official announcement	-0.145 (0.167)	-0.519 (0.399)	-0.007 (0.141)	-0.180 (0.448)
1 day after	0.120 (0.167)	0.613 (0.399)	-0.001 (0.141)	0.793 (0.448)
2 days after	-0.147 (0.167)	-0.494 (0.399)	-0.086 (0.141)	-0.565 (0.448)
3 days after	-0.163 (0.167)	-0.645 (0.399)	-0.092* (0.141)	-0.393 (0.448)
4 days after	-0.111 (0.167)	1.293*** (0.399)	0.009 (0.141)	0.377* (0.448)
5 days after	-0.046 (0.167)	-0.131 (0.399)	-0.109 (0.141)	-0.808* (0.448)
Inventory	-0.000 (0.006)	-0.000 (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Time to delivery	-0.000** (0.000)	-0.000*** (0.000)	-0.000 (0.000)	-0.000** (0.000)
Interest Rate	-0.027*** (0.006)	-0.209*** (0.017)	-0.001 (0.010)	-0.043*** (0.013)
Constant	0.244*** (0.012)	1.387*** (0.043)	0.251*** (0.004)	1.219*** (0.032)
Observations	4,451	4,451	5,315	5,315
Adjusted R^2	0.288	0.475	0.347	0.508
F statistics	119.3	269.9	189.2	366.4
RSET Test	3.767	0.063	3.157	1.217

*p<0.1; **p<0.05; ***p<0.01

Table 3 presents the results of the two-stage GLS estimation, assessing the official announcement effect on both corn and soybean futures contracts. The analysis includes both absolute close-to-open returns (reflecting overnight volatility) and absolute close-to-close returns (capturing volatility over the entire trading day).

Table 4: Results for the Government Program Pre-official announcement Effect on Absolute Commodity Returns

	Corn		Soybeans	
	Absolute close-to-open return	Absolute close-to-close return	Absolute close-to-open return	Absolute close-to-close return
5 days before	0.293** (0.149)	0.714* (0.429)	-0.151 (0.129)	-0.721 (0.470)
4 days before	-0.140 (0.149)	-0.172 (0.429)	0.091 (0.129)	1.271*** (0.470)
3 days before	-0.128 (0.149)	-0.608 (0.429)	0.008 (0.129)	-0.813* (0.470)
2 days before	-0.170 (0.149)	-0.055 (0.429)	-0.177 (0.129)	0.140 (0.470)
1 day before	-0.085 (0.149)	-0.623 (0.429)	0.070 (0.129)	0.657 (0.470)
Pre-official announcement	0.112 (0.149)	0.945** (0.429)	0.028 (0.129)	1.301*** (0.470)
1 day after	-0.104 (0.149)	-0.309 (0.429)	-0.068 (0.129)	0.025 (0.470)
2 days after	-0.035 (0.149)	-0.694 (0.429)	-0.137 (0.129)	-0.434** (0.172)
3 days after	0.127 (0.149)	1.193*** (0.429)	-0.026 (0.129)	0.019 (0.263)
4 days after	0.036 (0.149)	0.756* (0.429)	-0.104 (0.129)	-0.436* (0.263)
5 days after	0.255 (0.149)	2.465*** (0.429)	-0.034 (0.129)	0.414 (0.270)
Inventory	0.000** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.013)
Time to delivery	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Interest Rate	-0.029*** (0.006)	-0.212*** (0.035)	-0.006 (0.004)	-0.044 (0.032)
Constant	0.264*** (0.012)	1.385*** (0.043)	1.189*** (0.030)	1.218*** (0.192)
Observations	4,451	4,451	5,315	5,315
Adjusted R^2	0.286	0.479	0.343	0.508
F statistics	120	273.4	186.2	366.6
RESET	2.643	0.014	3.072	1.978

*p<0.1; **p<0.05; ***p<0.01

Table 4 presents the results of the two-stage GLS estimation, assessing the official pre-official announcement effect on both corn and soybean futures contracts. The analysis includes both absolute close-to-open returns (reflecting overnight volatility) and absolute close-to-close returns (capturing volatility over the entire trading day).

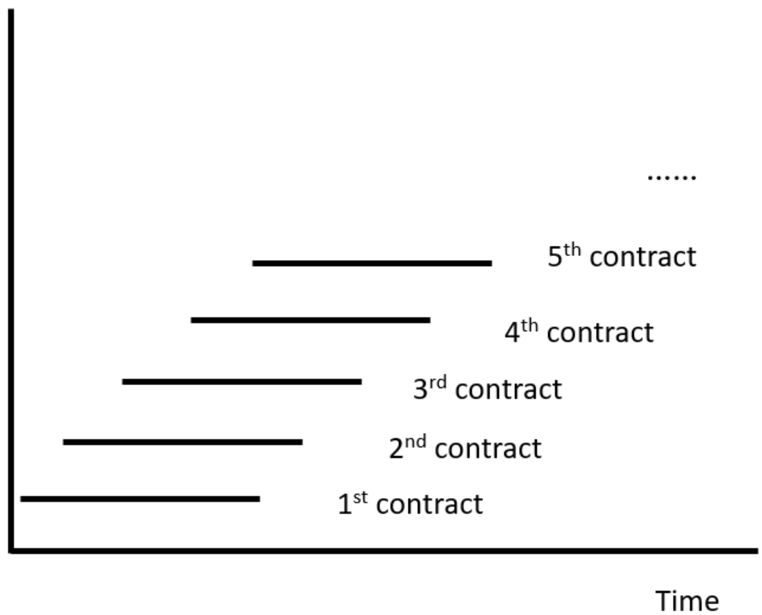

Figure 1: Futures Contract Positions on the Same Trading Day

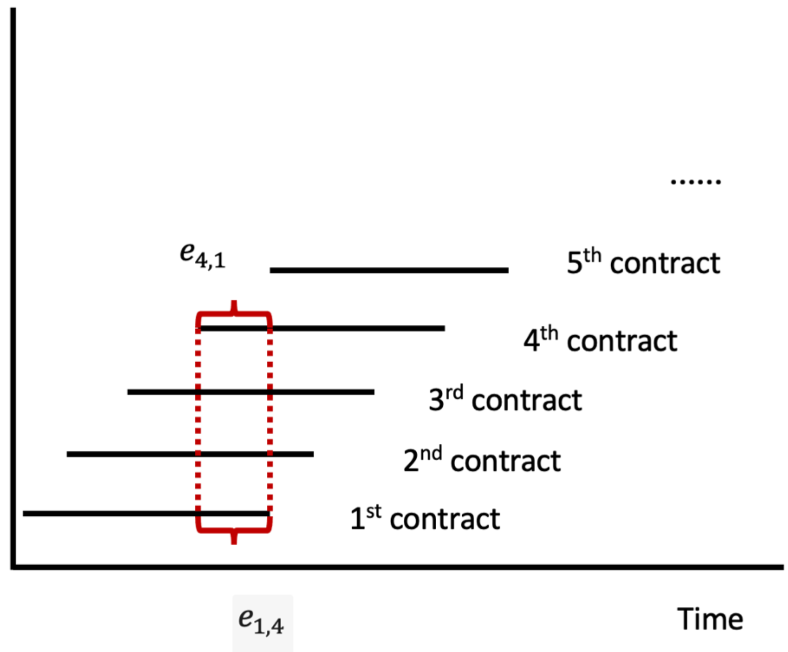

Figure 2: Overlapping Futures Contracts and Residuals

Appendix

1. Detailed Schedules for official and pre-official announcements

Table A1: Official announcements and Pre-official announcements of MFP and CFAP

Date	Program	Details
June 25, 2018	Pre-official announcement for MFP	By former United States Secretary of Agriculture Sonny Perdue: " In the meantime, the president has instructed me to craft a strategy to support our farmers in the face of retaliatory tariffs. At the U.S. Department of Agriculture, we have tools at our disposal to support farmers faced with losses that might occur due to downturns in commodities markets. To this point, we have not unveiled our strategy, as it is not good practice to open our playbook while the opposing team is watching."[5]
July 24, 2018	Pre-official announcement for MFP	The Trump administration announced Tuesday that it will grant up to $12 billion in emergency aid to farmers hurt by retaliatory tariffs in the ongoing trade fight with China and other American trading partners.[6]
Aug 1, 2018	Pre-official announcement for MFP	USDA releases fact sheet for MFP program
Aug 27, 2018	2018 MFP	Official announcement of payment structure which included payments would be in tranches and rate of payment by commodity.
Dec 17, 2018	2018 MFP	Official announcement of second and final tranche payments.
July 25, 2019	2019 MFP	Official announcement of MFP 2019 payment structure which stated payments would be made in three tranches.
Nov 15, 2019	2019 MFP	Official announcement of second tranche of payments.
Feb 3, 2020	2019 MFP	Official announcement of the third and final tranche of payments.
Mar 27, 2020	Pre-official announcement for CFAP	U.S. Secretary of Agriculture Sonny Perdue "At USDA we will deliver relief assistance to farmers and ranchers as quickly as possible," said Secretary Perdue."[7]
April 17, 2020	CFAP 1	Official announcement of CFAP 1 and total amount allocated for the program.
May 14, 2020	CFAP 1	Release of cost-benefit analysis which included payment rate by commodity.
May 19, 2020	CFAP 1	The second release is about the CFAP 1 along with more details.

[5] Source: https://www.usatoday.com/story/opinion/2018/06/25/donald-trump-china-tariff-retaliation-intellectual-property-agriculture-farm-perdue-column/725447002/

[6] Source: https://www.usda.gov/media/press-releases/2018/07/24/usda-assists-farmers-impacted-unjustified-retaliation

[7] https://www.usda.gov/media/press-releases/2020/03/27/secretary-perdue-statement-coronavirus-rescue-package

Sept 15, 2020	Pre-official announcement for CFAP 2	Coronavirus Food Assistance Program 2 Cost-Benefit Analysis released.
Sept 18, 2020	CFAP 2	Official announcement of CFAP 2
Sept 15, 2020	CFAP 2	Release of cost-benefit analysis which included payment rate by commodity.

2. Durbin-Watson Test

Table A2:Range of DM Test Results for Serial Correlation

Tests	Absolute close-to-open return	Absolute close-to-close return
Official Announcement		
Corn	2.09-2.40	2.07-.25
Soybean	2.01-2.02	2.03-2.21
Pre-official Announcement		
Corn	2.09-2.40	2.07-2.25
Soybean	2.017-2.022	2.017-2.022

Table A2 presents the results of the Durbin–Watson test for all cases. We calculate one Durbin–Watson statistic for each of the 20 corn futures contracts and 25 soybean futures contracts. To confirm no serial correlation within each contract, the test statistic should be close to or greater than 2. For simplicity, we report the range of test statistics. Since all values exceed 2, we conclude that serial correlation has been effectively corrected in the first stage.

3. Nearest to Maturity Contracts

Table A3: Results for the Government Program Official announcement Effect on Absolute Commodity Returns (Nearest to Maturity)

	Corn		Soybeans	
	Absolute close-to-open return	Absolute close-to-close return	Absolute close-to-open return	Absolute close-to-close return
5 days before	0.365 (0.397)	0.117 (0.366)	1.216*** (0.332)	1.053*** (0.067)
4 days before	-0.522 (0.410)	-0.215 (0.271)	0.769 (0.255)	-0.367 (0.229)
3 days before	-0.437 (0.292)	-0.077 (0.241)	-0.355 (0.228)	-0.317 (0.210)
2 days before	-0.769 (0.543)	-0.574* (0.300)	-0.308 (0.294)	-0.072 (0.219)
1 day before	-0.392 (0.414)	-0.161 (0.285)	-0.451 (0.279)	-0.720 (0.208)
Official announcement	-0.149 (0.201)	0.150 (0.241)	-0.055 (0.221)	-0.042 (0.165)
1 day after	0.583 (0.433)	-0.449 (0.299)	-0.206 (0.266)	-0.269 (0.198)
2 days after	-0.295 (0.367)	-0.265 (0.366)	-0.349 (0.332)	-0.298 (0.248)
3 days after	-0.037 (0.415)	0.376 (0.271)	-0.418 (0.255)	-0.074 (0.190)
4 days after	-0.699** (0.253)	0.028 (0.250)	0.454 (0.228)	-0.353 (0.170)
5 days after	-0.513 (0.541)	-0.021 (0.318)	-0.006 (0.294)	0.035 (0.219)
Inventory	-0.000 (0.006)	-0.000 (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Time to delivery	-0.002 (0.001)	-0.001 (0.000)	-0.002*** (0.000)	-0.000** (0.000)
Interest Rate	-0.029 (0.007)	0.005 (0.037)	-0.053 (0.035)	0.091*** (0.026)
Constant	1.578*** (0.170)	1.017*** (0.081)	1.553*** (0.090)	1.053*** (0.067)
Observations	1,024	1,024	1,024	1,024
Adjusted R^2	0.004	0.011	0.058	0.065
F Statistics	1.329	2.801	5.52	6.092

*p<0.1; **p<0.05; ***p<0.01

4. Results for 5 event windows

Table A4a: Results for the Government Program Official announcement Effect on Absolute Commodity Returns

	Corn		Soybeans	
	Absolute close-to-open return	Absolute close-to-close return	Absolute close-to-open return	Absolute close-to-close return
2 days before	-0.092	0.617	-0.013	0.910*
	(0.167)	(0.392)	(0.134)	(0.410)
1 day before	-0.061	-0.319	-0.145	-0.703
	(0.167)	(0.392)	(0.134)	(0.410)
Official announcement	-0.143	-0.525	-0.219	-0.225
	(0.167)	(0.392)	(0.134)	(0.410)
1 day after	0.122	0.607	-0.074	0.574
	(0.167)	(0.392)	(0.134)	(0.410)
2 days after	-0.146	-0.501	-0.152	-0.522
	(0.167)	(0.392)	(0.134)	(0.410)
Inventory	0.000**	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Time to delivery	-0.000**	-0.000***	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Interest Rate	-0.028***	-0.205***	-0.005	-0.048***
	(0.006)	(0.017)	(0.005)	(0.013)
Constant	0.264***	1.378***	0.227***	1.091***
	(0.012)	(0.043)	(0.009)	(0.032)
Observations	4,451	4,451	5,315	5,315
Adjusted R^2	0.286	0.472	0.303	0.507
F statistics	198.8	443.3	233.9	531

*p<0.1; **p<0.05; ***p<0.01

Table A4b: Results for the Government Program Pre-Official announcement Effect on Absolute Commodity Returns

	Corn		Soybeans	
	Absolute close-to-open return	Absolute close-to-close return	Absolute close-to-open return	Absolute close-to-close return
2 days before	-0.125	0.067	-0.125	0.143
	(0.136)	(0.434)	(0.134)	(0.392)
1 day before	-0.111	0.631	-0.111	0.663
	(0.136)	(0.434)	(0.134)	(0.409)
Official announcement	0.004	0.932**	0.003	1.296***
	(0.136)	(0.434)	(0.134)	(0.409)
1 day after	-0.036	-0.322	-0.037	-0.023
	(0.136)	(0.434)	(0.134)	(0.409)
2 days after	-0.082	-0.702	-0.083	-0.742
	(0.136)	(0.434)	(0.134)	(0.409)
Inventory	0.000**	-0.000***	-0.000*	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Time to delivery	-0.000**	-0.000***	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Interest Rate	-0.045	-0.205***	-0.005	-0.057***
	(0.005)	(0.017)	(0.005)	(0.015)
Constant	0.228***	1.378***	0.228***	1.327***
	(0.009)	(0.049)	(0.010)	(0.049)
Observations	4,451	4,451	5,315	4,451
Adjusted R^2	0.303	0.502	0.303	0.502
F statistics	198.8	443.3	233.7	541.5

*p<0.1; **p<0.05; ***p<0.01