NCCC-134
APPLIED COMMODITY PRICE ANALYSIS, FORECASTING AND MARKET RISK MANAGEMENT

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Suggested citation format:
Swearingen, B. and J. P. Janzen. 2021. “Buying Time: The Effect of Market Facilitation Program Payments on the Supply of Grain Storage.” Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. [http://www.farmdoc.illinois.edu/nccc134].

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Paper prepared for the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, 2021.

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Buying Time: The Effect of Market Facilitation Program Payments on the Supply of Grain Storage

We estimate the impact that the Market Facilitation Program (MFP) payments had on farmers' willingness to store grain. Using a fixed effects model across multiple dimensions and state-level data on MFP, grain stocks, production, and export dependence, we address the role of the decrease in opportunity costs causing an increase in the willingness to store of farmers. Our analysis finds that MFP payments had a significant impact on grain storage by US farmers. In states with relatively higher payments at the marginal 10% increase in payments a 1.28% increase in on-farm inventories will occur holding all else constant. This explains that policies that increase access to financial capital can cause small increases to grain inventories.

Key words: Ad hoc payments; fixed effects; grain storage

1 Introduction

Between 2018 and 2020, the United States Department of Agriculture (USDA) made unprecedented direct payments to US farmers via a series of ad hoc programs. Among these were two rounds of payments under the Market Facilitation Program (MFP), an ad hoc farm program to "help farmers manage disrupted markets" and compensate farmers for "trade damage from unjustified retaliation" part of the larger US-China trade conflict. The MFP paid 8.5 billion and 14.5 billion dollars during the 2018-19 and 2019-20 crop marketing years, respectively, with payments concentrated to producers of major row crops, namely corn, cotton, sorghum, soybeans, and wheat. MFP payments had a significant impact on farm profitability, comprising 8 and 12 percent of net cash income for US farmers in calendar years 2018 and 2019.

We seek to understand what effect MFP payments had on farmer decision making. Both rounds of MFP payments were designed to avoid biasing farmers' planting and production decisions by determining payments after the planting period (in 2018) or basing payment amounts on planted acres of all crops (in 2019). In the absence of production effects, MFP may have had unintended impacts on farmer grain marketing decisions, specifically affecting the willingness to hold grain inventories.

We hypothesize that MFP payments reduced the opportunity cost of foregone grain sales and increased on-farm inventories. Working's Theory of Storage models inventory holding as an equilibrium between storage demand, a function of current and expected future commodity availability, and storage supply determined by the marginal cost of holding inventories. It suggests the marginal cost of storage is in part a function of the opportunity cost of having grain tied up in storage. This opportunity cost is the interest that a producer could have earned, or the financing cost foregone by selling at harvest instead of storing. MFP payments may have lowered effective interest costs by enabling farmers to pay off existing loans or borrow less. For example, according to the Federal Reserve Bank of Kansas City, "agricultural lending declined during the second half of 2019" and "reduced loan demand likely also was due to an increase in revenue from government payments" (Kauffman & Kreitman, 2019).

Shifts in the supply of storage caused by MFP payments are difficult to identify because declining export demand due to the trade war may have caused a simultaneous increase in storage demand. Since the MFP-related supply shock and the trade-war induced demand shock are roughly contemporaneous, identifying the effect of the supply shock requires that we isolate variation in MFP that is uncorrelated with the market shock caused by the trade war. To do so, we exploit the fact that MFP payment calculations for a given commodity were the same across all farms, while the effect of the trade war on commodity prices varied across space.

Using quarterly state-level grain stocks data for corn, soybeans, wheat, and sorghum gathered from the National Agricultural Statistics Service for 2014-15 through 2019-20 marketing years, we estimate the impact of MFP on on-farm inventory levels in the 2018-19 and 2019-20 marketing years. We use a fixed effects model with multiple dimensions where the outcome of interest is on-farm inventory in a given state for a given commodity in a given quarter of a given marketing year. The (continuous) treatment variable is the MFP payment amount for that state-commodity-marketing year. The goal of adding additional fixed effects and confounders is to alleviate the bias of MFP impact related to the trade war demand shock. To control for common shocks in storage behavior across states and over time, we include marketing-year and state fixed effects. To account for differences in storage behavior across crops, including differences in storage seasonality, we also include commodity by quarter fixed effects.

Our econometric model is analogous to a difference-in-difference study where each state and commodity has differing exposure level to the treatment variable. The effect of interest is identified by differences in the change in inventory over time between states that received proportionally more MFP dollars relative to those that received proportionally less. To adjust for confounding demand shifters, we include state-level annual crop production and quarterly state-level futures-cash basis as covariates. To assess whether our estimated effect is specific to farmers who received MFP payments, we test the hypothesis that only on-farm inventories were impacted by MFP. This falsification test is estimating the same econometric model but changes the outcome of interest to be off-farm inventories for a state-commodity-marketing year-quarter.

We find MFP payments had a significant impact on grain storage by US farmers. In our baseline model, states that receive higher payments will see a 0.128% increase in on-farm inventories with a 1% increase in MFP payments. The falsification test supports the hypothesis that this effect is specific to farmers and on-farm inventories. This tells us that a farmers' access to financial capital in the form of government payments allows for them to be able to "buy time" and store until prices are more desirable.

This study is unique as it provides a baseline analysis to how farmers' storage behavior is impacted by policies that provide greater access to financial capital. Grain storage is a key tool in farmers' marketing decisions and provides flexibility to the supply chain system. In periods of low inventories, grain prices have been found to be more volatile. It is important to analyze how policies impact farmer storage behavior as storage plays a significant role in the financial market. With the increase in ad hoc payments the last few years, these could become a large source of farm income for producers. It is crucial to stay alert as significant changes in inventories could put pressure on the financial market for grain producers.

2 Background

This section provides background information on the trade war, ad hoc government payments, and overall marketing and storage decisions of grain producers. Figure 1 shows how these events unfold across time from 2018-2020. By looking into these three categories more closely, we get a clearer picture of the impacts to grain producers during the 2018-19 and 2019-20 marketing years.

2.1 Trade War

On June 28, 2016, Former President Trump embarks on a plan to counter unfair trade practices with China (Reuters Staff, 2020). This was just the beginning of trade issues between the United States and China. The trade war started esculating more after Former President Trump announced tariffs on steel and alumninum of 25% and 10%, respectively. China relatiated and their additional tariffs were disproportonally targeting US agriculture. During the September-July period of the 2018-19 marketing year, U.S soybean exports to China saw a 65% decrease (Adjemian et. al, 2019). This decrease in exports really took a toll on futures prices.

The June 15th announcement can be seen as a crucial turning point due to corn prices falling nearly 7% while soybean prices dropped more than 10% over then next month (Swanson et. al, 2018). This announcement included a 25% tariff on $34 billion in U.S. products, including soybeans and pork. Janzen and Hendricks (2020) suggest that "while we cannot attribute all of the decrease in forcaseted prices due to the trade conflict, it suggests the trade conflict may have hurt some commodities more than others".

Not only were futures prices impacted by the trade war, but the loss of exports impacted basis values. Adjemian et. al (2019) studies how the tariff retailiation impacted soybean and corn basis values. They explain that basis was impacted differently across regions, commodities, and marketing years. Soybean basis values were more impacted in the areas closer to export ports or terminals as it was more difficult for them to find an outlet for their shipments. Basis values are also impacted by large changes in production values. While both corn and soybeans both had historically large production in 2018-19 MY, soybeans suffered historicaly weak basis levels following tariff retaliation, while corn did not (Adjemian et al, 2019). This difference in production also is what makes these basis values different across marketing years. The 2019-20 marketing year exhibited adverse palnting conditions leading to a smaller crop and tighter inventory conditions. These conditions will contribute to a stronger basis during this marketing year. The variation in basis across regions, commodities, and marketing years will allow us to use it to estimate the potential impact that these tariffs had on the demand for grain storage.

The imapct to commodity prices and loss of exports led President Trump to instruct Secretary Purdue to implement a relief package to farmers. The Market Faciliation Program was announced to the country on July 24th, 2018 with more specific details coming later on August 27th (FSA New Releases). This program provided ad hoc payments to farmers and ranchers during the 2018-19 and 2019-20 marketing years.

2.2 Ad Hoc Government Payments

Over the last few years ad hoc government payments have increased significantly. Ad hoc farm payments are those that are not currently part of the current farm safety net. The primary purpose of these government payments is to support farm income. In the years 2019 and 2020, "farm payments surged to post-1973 highs, averaging $23.2 billion and 84% are ad hoc payments" (Zulauf et. al, 2020). Most of this increase is from the Market Facilitation Program (MFP) and Coronavirus Food Assistance Program (CFAP). Figure 1 provides a timeline of these announcements and rounds of payments for both MFP and CFAP. This study specifically looks at the impact that MFP had on grain storage, but the framework could apply to any ad hoc government payment.

The MFP program saw two different rounds of these payments. The payments released during the 2018-19 marketing years are referred to as MFP1. The payments released during the 2019-20 marketing years are referred to as MFP2. There are quite a few differences between these two programs. They were calculated differently, included different commodities, and were announced at different times during the marketing year.

As mentioned earlier, MFP1 was announced on July 24th, 2018 but details did not get released for another month. At this point, farmers knew how much overall they were paying out for this program and that the Farm Service Agency was administering the payments. They were also told that the program covered soybeans, sorghum, corn, wheat, cotton, dairy, and hog producers. MFP1 provided 8.5 billion dollars to farmers in two different tranches. Farmers were not guaranteed the second tranche and it was only going to be paid out if a trade tensions were not resolved.

The MFP1 payments were calculated using a national commodity-specific MFP payment rate multiplied by the 2018 farm-level harvested production of each crop. These payment rates were based on estimated total direct trade damage for each commodity. The application process was open until Feb. 14, 2019 to allow enough time for producers to get their harvest in. The first payments starting on Sept. 27th and covered 50% of the expected payments, the second half came later after December 17th. This shows that the cash flow happened during the fourth quarter of 2018. Therefore, the impact of this program is analyzed during the 2018-19 marketing year. The MFP1 program was tailored more towards soybeans as they were the commodity directly related to loss of exports. They did not account for the loss in the futures market for other commodities in this round.

The MFP2 payments were announced on May 23rd, 2019. This announcement fell during planting for corn, soybeans, spring wheat, and sorghum. Due to an extremely wet planting season, most of the Midwest was still planting and debating on taking prevent plant for some of their acres. This is important to know as MFP2 payments were calculated based on 2019 farm-level acres planted of any crop that was eligible. The MFP2 payment rate was calculated and released on a county-level basis. Each producer could use their county payment rate and multiply it by their estimated planted acres for the 2019-20 marketing year. Prevent plant acres were included in this round of payments, but they received a lower rate. Since this round of payments were paid out on a planted acres basis, the impact across commodities were a lot more even. It also did not require a specific commodity to be planted on the acreage. This round also had more crops that were covered under this round compared to MFP1.

MFP2 provided 14.5 billion dollars to producers in three different tranches. The only one that was certain was the first round that provided 50% of the estimated payment. The sign up for MFP2 was open from August 19th to December 20th. This allowed producers plenty of time to get their numbers on planted acres. This also makes is challenging though to understand when farmers received these payments as they could have waited till last minute to sign-up. The second and third tranches were announced on November 15th and February 3rd, respectively. In general, most of the payments of MFP2 were received during the fourth quarter of 2019. Producers knew about it during the 3rd quarter of 2019 and might have impacted some of their decisions, but for the purpose of this study the impact will take place over the course of the 2019-20 marketing year.

The similarity between these two rounds of payments is that the USDA worked hard to ensure that these payments did not impact farmers' production decisions. They announced them after the majority of the planting decisions were made or in progress. MFP2 might have had a slight impact in production decisions due to the timing of the announcement and prevent plant stipulations, but overall, not a lot. The next section explains how the timeline of these payments align with when farmers' marketing and storage decisions are made.

2.3 Marketing & Storage Decisions

Figure 1 also displays when marketing and storage decisions are made by producers. The decisions align with each commodity's marketing year. In this study, the marketing years are defined as follows:

- Fall Harvest Crops (Corn, Soybeans, Sorghum):
    - Marketing Year (t - t+1) = Sept 1st, t – August 31st, t+1
    - 2018 Marketing Year = Sept 1st, 2018 – August 31st, 2019
- Summer Harvest Crops (Wheat):
    - Marketing Year (t – t+1) = June 1st, t to May 31st, t+1
    - 2018 Marketing Year = June 1st, 2018 – May 31st, 2019

The first quarter of each marketing year aligns when the crops harvest is completed. This is also when the crops initial stocks are decided based on harvested production. A lot of the farmers' storage decisions take place at harvest. They are deciding where and how much grain to store. The rest of the marketing year, producers make decisions on when to sell based on when they need the cash flow and when they have the time to complete their sale contracts. By the end of the marketing year, farmers typically empty their grain bins unless there is a carry in the market. This allows for the ending stocks to be decided during the last quarter of the marketing year.

When it comes to when and why producers store, it is important to analyze the theory of grain storage. The next section will provide a literature review on the theory of grain storage. This will provide the necessary information needed to understand how the MFP payments could impact farmer storage behavior.

Figure 1: 2018-2020 Timeline of Events

	Trade War	Ad Hoc Government Payments	Fall Harvest Marketing Decisions	Summer Harvest Marketing Decisions
March – May 2018	•March 8th: US tariffs on steel & aluminum •April 2nd: China tariffs on US products, soybeans		• April: Beginning predictions for 2018-19 production	
June - Aug 2018	•June 15th: US & China announce more tariffs •Corn & soybean prices fell 7% & >10%, respectively	• July 24th: USDA announced Idea of MFP • Aug. 27th: MFP1 – Details Announced	• Producers prepare their storage facilities for harvest production	• June 1st: Wheat ending stocks for 2017-18 MY
Sept. – Nov. 2018	• US announced 10% tariffs on Chinese imports • China taxes $60 billion of U.S goods	• Sept.4 - Feb 14th: MFP 1 – 1st Round	• Fall Harvest 18-19MY begins • Sept 1st: Fall harvest ending stocks 17-18MY	• Sept. 1st: Wheat Crop initial stocks for the 2018-19MY
Dec. 2018- Feb. 2019	• US & China agree to a 90-day halt to new tariffs	• Dec. 17 – Feb 14th: MFP 1 – 2nd Round	• Jan: 2018-19 MY Production numbers released • Dec 1st: initial stocks decided for 2018-19MY	• Jan: 2018-19 MY Production numbers released • Jan: 2019-20 MY Production estimates begin
March - May 2019	• May 1st: craft a 150-page trade deal agreement, Beijing backtracks on deal	• May 23rd: MFP 2 – Details Announced	• Beginning predictions for 2019-20 fall production	
June – Aug. 2019	• June 29th: agree to no new tariffs • Quickly changes to more tariffs	• Aug 19th – Dec. 20th: MFP 2 – 1st Round • Prevent plant eligibility for MFP announced	• Producers prepare their storage facilities for harvest production	• June 1st: 2018-19 Wheat ending stocks decided
Sept. – Nov. 2019	• Oct. 11th: Trump announces Phase 1 Trade Deal	• Nov. 18th – Dec 20th: MFP 2 – 2nd Round	• Fall Harvest 19-20 MY • Sept. 1st: fall harvest ending stocks 18-19MY	• Sept 1st: Wheat crop initial stocks for the 2019-20MY
Dec. 2019 – Feb. 2020	• Jan 15th: US, China sign phase one trade deal • Feb.: Both countries halve tariffs in line w/ deal	• Feb. 3rd – Feb. 22nd: MFP 2 – 3rd Round	• Dec. 1st: 2019-20 MY Fall crop initial stocks • Jan: 2019-20 MY Production numbers released	• Jan: 2019-20 MY Production numbers released • Jan: 2020-21 MY Production estimates begin
March – May 2020	• China-US reaffirm their phase one trade deal despite the COVID-19 Pandemic	• May 19th: CFAP payments announced	• April: Beginning predictions for 2020-21 fall production	
June – Aug 2020	• July 14th: China books record deal for US corn • Phase 1 Trade deal revisited and are optimistic	• May 16 – Sept. 11: CFAP 1 - Payments		• June 1st: 2019-20 MY Wheat ending stocks decided

Sources: Reuters Staff, 2020; Wong & Koty, 2020; Swanson et. al, 2018; USDA-Press Releases, 2020
Notes: This study specifically looks at only the impact of MFP, but this visual includes CFAP payments to get a round picture of these ad hoc programs during the 2018-2020 years.

3 Grain Storage Theory

A unique aspect in the production of grains is seasonality and the need to make the supply of commodities flow relatively stable (Brennan, 1958). This aspect creates a need for grain to be held in storage from harvest till the commodity is used. The theory of grain storage has been studied extensively and provides a framework for understanding how stockholders may have responded to the increase in ad hoc payments.

3.1 Supply

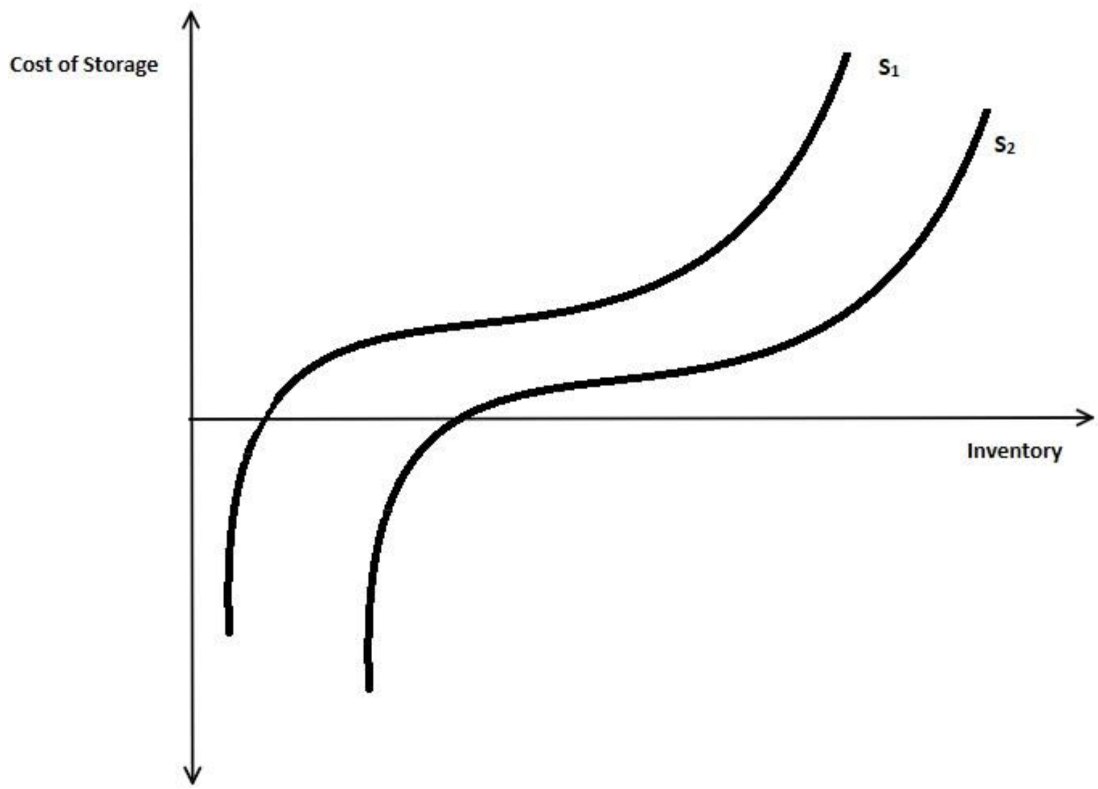
In a competitive market, the supply curve is also the marginal cost curve. The theory of storage explains that producers will store if their marginal cost of storing is equal to the anticipated price difference between now and the time the commodity is removed from storage and sold. Working (1949) recognized that the futures market provides stockholders a known return for storage. "The inter-temporal price spread is the price of storage since the difference between the futures and the spot price can be interpreted as the marginal cost of storing the commodity" (Carter & Revoredo-Giha, 2009). The Working curve demonstrates the supply of storage at varying price spreads. This curve includes the opportunity for producers to hold inventories even under negative price spreads. A movement along the Working curve explains that as the price of storage increases, or the price spread widens, then the quantity of inventory increases due to the potential for higher returns. Figure 2 shows the standard shape of the Working curve.

The marginal cost of storing a commodity includes factors such as interest charges, rent on a facility, and loading and unloading charges (Carter & Revoredo-Giha, 2009). These are factors that are not explicitly stated on the y-axis. Therefore, these are the factors that will cause a shift in the Working curve. In the past it was more common to view the supply of storage function as relatively stable (i.e. the variables changed relatively little). The main factor that causes the shifts in the supply curve are when interest rates change. Interest rates are used to give an approximation of the opportunity cost of keeping grain tied up in storage. Gardner & Lopez, 1996 finds that an interest-rate subsidy increases the amount of inventory carried over to the next period. This means that as interest-rates decrease there is a shift in the Working curve to the right. This effect is displayed in figure 2 from S_1 to S_2. Other factors that would cause this same shift would be a decrease on the rent for a facility or a decrease on loading and unloading charges.

Working's theory of price storage allows for stockholders to store when returns are negative due to a Kaldor's *convenience yield* to store (Kaldor, 1939). This is why the shape of the working curve in figure 2 displays the opportunity for producers to hold inventories even in negative returns. This assumption is very "controversial because it appears to contradict inter-temporal arbitrage conditions" (Joseph et al, 2015). This condition means that stockholders will only hold inventory if the spread between future and cash price is positive or display a positive return. Various studies have challenged the assumption of convenience yield (Wright & Williams, 1989; Brennan et al. 1997). Other economists have explained the theory of storage and assume that stockholders will not store if their return is negative (Eastham, 1939). Eastham (1939) explains that stockholders are heterogenous meaning that processors and speculators store differently. He assumes that speculators will not store if their risk premium is negative. This makes sense as speculators carry a risk by storing their grain and they will not take on the risk if they believe their profits would be negative. Brennan (1958) combats this assumption by explaining that “the convenience yield is attributed to the advantage of being able to fill orders quickly or cheaply in the case of an “unexpected” increase in demand.”

Whether there is a convenience yield is only partially relevant. As explained earlier, farmers both store in their own facilities to manage their risk and wait for higher prices, but they also store if they use their own crop harvest to feed their livestock. This means producers might store even when the returns are negative just to leverage the market or use for their own operations. The reason that convenience yield in this situation is not as critical though is due to the large amounts of inventories over the past few years. In years when there is a lot of grain held in storage, there are smaller convenience yields as prices fluctuate less under large amounts of inventories. This allows us to believe we are not on the range of the curve where convenience yield dominates.

Figure 2: Supply of Storage Relationship (Adapted from Tomek & Kaiser, 2014)



3.2 Demand

The demand for storage also affects stockholders' storage behavior. Brennan (1958) explains that "the demand for storage of a commodity can be derived from the demand for its consumption". The key parts that make up consumption of a commodity are the stocks at the end of the period *t-1* (S_{t-1}), the production in period *t* (X_t), and the stocks at the end of *t* (S_t). The relationship between these variables is outline below, where P_t is the price in period *t* (Brennan, 1958). Equation 1 provides us the consumption demand function for a storable commodity in period *t*.

Equation 1: Consumption Demand Function for a Storable Commodity

$$P_t = f_t(S_{t-1} + X_t - S_t)$$

By using equation 1, we can derive the demand for storage given the difference in the demand for the commodity between two periods. Equation 2 demonstrates this demand for storage between two periods. It is represented by the difference in prices between periods *t+1* and *t*.

Equation 2: Demand for Grain Stocks between Two Periods

$$P_{t+1} - P_t = f_{t+1}(S_t + X_{t+1} - S_{t+1}) - f_t(S_{t-1} + X_t - S_t)$$

By looking at equation 2, it is a little difficult to see how this demand curve might look. Carter (2018) explains that this demand for grain stocks curve can be considered downward sloping. This can be explained intuitively through an example. If there are more stocks carried out of period *t* into *t+1*, this implies there is more for sale in period *t+1* than in period *t*. This situation will increase the price in period *t* relatively to period *t+1* causing a weaker price spread, $P_{t+1} – P_t$. The standard shape of the demand curve can be seen in figure 3

In order to understand what causes a shift in demand for inventories, we must look at each factor that goes into equation 2. The demand for grain stocks show that changes in production, anticipated production, and the carry out level of stocks shift the demand for storage. Below are the potential shifters that would explain a shift in the demand curve to the right or upward.

- Decrease in the anticipated production (X_{t+1})
- Increase in production (X_t)
- Increase in stocks carried out of t (S_{t+1})

This shift is shown in figure 3 from D_1 to D_2.

3.3 Equilibrium Model

The optimum price and quantity are determined when the supply of storage intersects the demand or consumption of storage. A supply of storage shift to the right results in a decrease in the price spread or basis between periods. When the demand curve shifts it depends on what area it is shifting to and from on the supply of storage curve. If the demand curve shifts in the horizontal region a price impact is less likely than an extreme shift to the right or left (Tomek &

Kaiser, 2014). The equilibrium or intersection point explains the quantity that stockholders are willing to store at a given price differential is exactly equal the quantity demanded for inventories. In other words, "the equilibrium requires that the net cost of storage must equal the price of storage" (Carter, 2018).

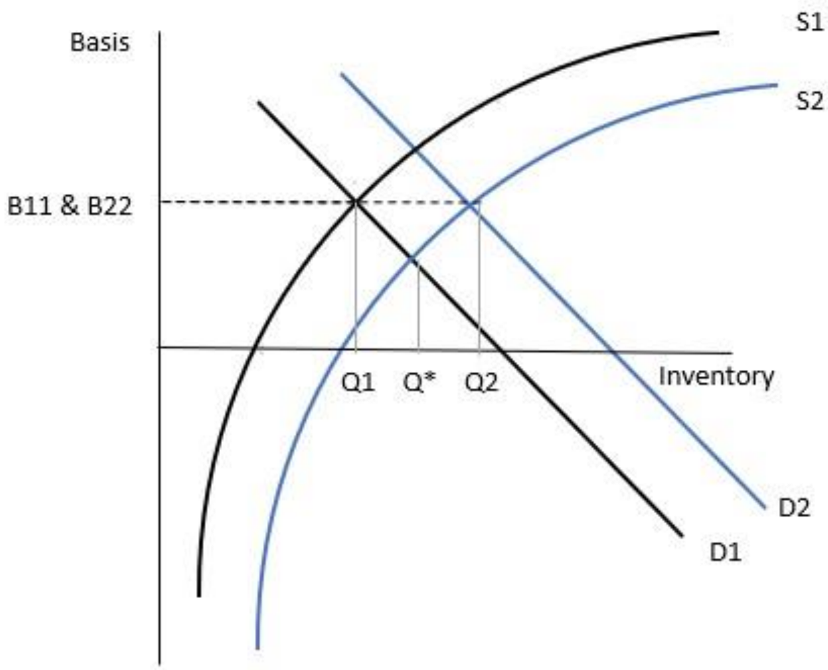
The price of storage can also be seen as the difference between cash and futures prices (Tomek & Kaiser, 2014). Basis provides producers with a closer look at what the return of storage is at a local level. Basis varies across states and commodities due to changes in local factors. These factors include availability of transportation, quality differences, and local supply and demand conditions for the commodity. For these reasons, the equilibrium model in figure 3 will include basis as the measure of the price of storage.

3.4 Market Facilitation Program Impact

This study uses the theory of storage outlined above and relates it to the potential impacts that the Market Facilitation Program had on inventory levels or stockholder behavior. As mentioned earlier, MFP provided payments directly to the commodity producers. Given this information, this study looks at how on-farm inventories were impacted through these ad hoc payments. This program was created as a relief strategy due to the loss of exports and decreases in commodity prices as a result of the trade war with China. Due to the contemporaneous impacts of the trade war and MFP, the trade war impacts to a farmers' willingness to store will also be analyzed.

Based on the timeline in figure 1, this study considers the impact of the program begins when farmers start to receive the extra cash flow in payments. The extra cash flow results in a decrease in opportunity cost as farmers have that additional cash that they would have had to sale their commodity to receive. We will assume a single effect for each marketing year. The 2018 MFP Payments (MFP1) impacted farmers during the 2018-19 marketing year. For 2019 MFP payments (MFP2) the impact is considered to be any quarter during the 2019-20 markeitng year.

Figure 3: Storage Supply & Demand Relationship (Adapted from Tomek & Kaiser, 2014)



This study aims to isolate the effect that MFP had only on the supply of storage. This is due to only farmers receiving additional payments through the Market Facilitation Program. Those producers that received payments were able to make payments on their operating loans without having to sell grain for cash flow. This decreases a farmers' opportunity cost to store grain due to the additional cash flow. Interest rates are used to give an approximation of the opportunity cost of keeping grain tied up in storage. The supply of storage curve represents the aggregate supply of storage, therefore not all farmers needed to be liquidity constrained just a few to see this impact. Based on this theory, this study views that these payments act like an interest-rate subsidy. As explained earlier in this section an interest-rate subsidy shifts the supply of storage curve to the right. This relationship can be depicted in figure 3 from S_1 to S_2.

According to the USDA World Agriculture Supply and Demand Estimates report that was published on January 10, 2020, the change in US ending stocks for soybeans increased by 471 million bushels from January 2017 to January 2018 (Office of Chief Economist, 2020). The decrease in exports accounted for 82% of this increase in ending stocks. Producers and end users had to make room for a larger carryout since they did not have a market to which they could sell their products. The anticipation of the increase in inventories carried out of 2018 (S_{2019}) likely shifted the demand for storage upward.

Figure 3 depicts the supply and demand for storage situation that is explained in this section. The pre-MFP curves have the subscript 1 while the post-MFP curves have the subscript 2. These shifts are drawn in a way that shows that basis values were unaffected by the shifts in supply and demand for inventories. The reason behind this is to show what the empirical model in the next section is trying to predict. The goal of the empirical model is to show what the change in inventories is from Q_1 to Q^*, that is the change in inventory purely caused by the supply shift. This change demonstrates the shift in supply predicted to be due to MFP while controlling for potential demand confounders such as production and basis. The following sections will explain more in depth on the dataset and the methodology behind this model.

4 Data & Summary Statistics

In this study, we construct a panel dataset of grain inventories, government payments, and other variables from multiple sources. The granularity of the data are limited by the availability of data on grain inventories which are reported for states, commodities, and location of storage at a quarterly frequency. This section describes how the data are collected and structured.

4.1 Variables & Sources

Grain inventories are the main outcome of interest. The National Agricultural Statistics Service releases a quarterly *Grain Stocks* report containing inventory data for each state and commodity. This report is released in January, March, June, and September, but measures the inventory levels on the survey end dates which are the 1st of December, 1st of March, 1st of June, and 1st of September. This report contains inventory levels for corn, sorghum, oat, barley, wheat, soybeans, sunflowers, chickpeas, peas, and lentils. This study will specifically look at corn, sorghum, wheat, and soybeans inventories from Sept. 2014 – Sept. 2020, since these crops are the largest by volume and received substantial MFP payments. We specifically look at this time period as it limits the amount of structural changes in the grain industry that could impact the analysis if the window were wider.

The inventory data are also broken into two different types of inventory, on- and off-farm. On-farm inventories are defined as grain held in "all bins, cribs, sheds, and other structures located on farms" (USDA, 2019). NASS-USDA gathers on-farm inventory data through an on-farm stocks survey to a sample of producers. Each quarter these producers are asked to provide the amount of grain stored on their operations as of the survey end dates listed above. The off-farm stocks are estimated through a survey of all known commercial grain facilities. NASS attempts to get a report from each facility and makes estimates for missing facilities to make the survey complete. In general off-farm inventories are measured more precisely.

The other variable that is pulled from NASS is the annual production for each commodity and state. This variable is gathered for corn, soybeans, sorghum, and wheat from the calendar years 2015-2020. Production data are gathered and estimated monthly through the *Crop Production* report. The final estimate for the marketing year is released in January.

The main explanatory variables in the data are government payments to farmers, specifically payments made through the two rounds of Market Facilitation Program (MFP1 and MFP2). MFP1 payment data was gathered through a Freedom of Information Act request. These data are at a county-commodity level for all counties. These payments were aggregated to a state-commodity level by summing up all county-level payments by commodity.

MFP2 payments are manually calculated using data on crop acres and the MFP2 payment formula provided by the USDA (USDA, 2019). USDA calculated MFP2 payments using a county-specific rate per acre planted. The same rate applies to all eligible crops in a county, regardless of which crop was planted. The total potential MFP payment for a non-specialty crops are the farmers' 2019 planted acres planted multiplied by the county payment rate. The USDA based the acres planted off those reported to Farm Service Agency. We collect data on 2019 FSA acreage that includes all eligible crops in the MFP program at a county level. Using the county level acreage data, we can multiply the acreage level by the county payment rate to arrive at a county-level MFP2 payment. The county level payment rates were obtained from David Widmar via personal communication and align with FSA's published rates. Like MFP1 payments, the payments are then aggregated to a state-commodity level by summing up all county-level payments by commodity.

The third part of the panel data set consists of futures price and cash price data from the Bloomberg terminal. The daily settlement prices of the nearby futures contract are gathered for corn, soybeans, and wheat. The nearby futures contracts are those with the closest settlement date. This allows us to analyze what the market was worth on a specific day rather than the other contracts predicting what the commodity is worth in the future. The corn settlement price is considered the sorghum settlement price for the purpose of our analysis and in line with common commercial practice.

The daily cash price dataset contains the average state-level cash price from the elevators that report their bids to Bloomberg. This dataset provides more state-level observations and a separate price for sorghum than the price received data from USDA-NASS. This dataset also allows us to match specifically to each date based on the survey end date of the *Grain Stocks* report (March 1st, June 1st, etc.). The Bloomberg cash price data set also includes separate wheat observations based on the type of wheat grown to match with the different future exchanges and contracts more accurately.

The futures and cash price data are matched with the type of wheat grown most abundantly in each state. To determine which type of wheat is grown the most, a 5-year production average from NASS is used. The type of wheat is then paired with its' futures contract. The type of wheat that is traded on each future exchange is as follows: hard red wheat is traded off the Kansas City Board of Trade, soft red and soft white are traded on the Chicago Board of Trade, and hard red spring is traded off the Minneapolis Board of Trade. Table A-1 in the Appendix shows what type of wheat is grown the most using a 5-year production average from USDA-NASS.

The inventory dataset is the base in creating the panel dataset. The production data are merged by lagging it to match the crops' respective marketing year. This means the production numbers that are reported on January in year $t+1$ are considered the production values for the marketing year t-$t+1$. Each crops respective marketing years are outlined in the background section.

The start of each quarter of the marketing year aligns with the survey end dates for the grain stocks survey (March 1, June 1, Sept. 1, Dec. 1). This allows the settlement and cash price to be merged with the same dates. If the 1st of the quarter falls when trading is closed, it will be matched with the previous settlement price available. The nearby settlement price is subtracted from the cash price to create the future-cash basis variable after merging. The MFP payment information is also merged with the respective marketing year. The impact to a producers' opportunity cost to store would be based on when the extra cash flow was received. These payments were released throughout both marketing years. The full payment amount in each state is allocated to each quarter of that marketing year.

The reason we allocate the MFP payments across all quarters of the marketing year rather than when they received their payments is due to nature of how grain stocks are calculated. For example, if a farmer stores more at harvest time due to receiving these payments, the stocks for the following quarters of the marketing year can not be anymore than the previous quarter. Therefore, there could be an increase across all quarters. The extra cash flow can also be spread out over this full period of time resulting in a lower opportunity cost in all quarters.

After each part is merged this allows us to have an unbalanced panel dataset from September 2014 – September 2020 with state, commodity, marketing year, quarter, and storage location dimensions. Each quarterly observation in this dataset aligns with the *Grain Stocks* survey end dates (March 1, June 1, Sept. 1, and Dec. 1).

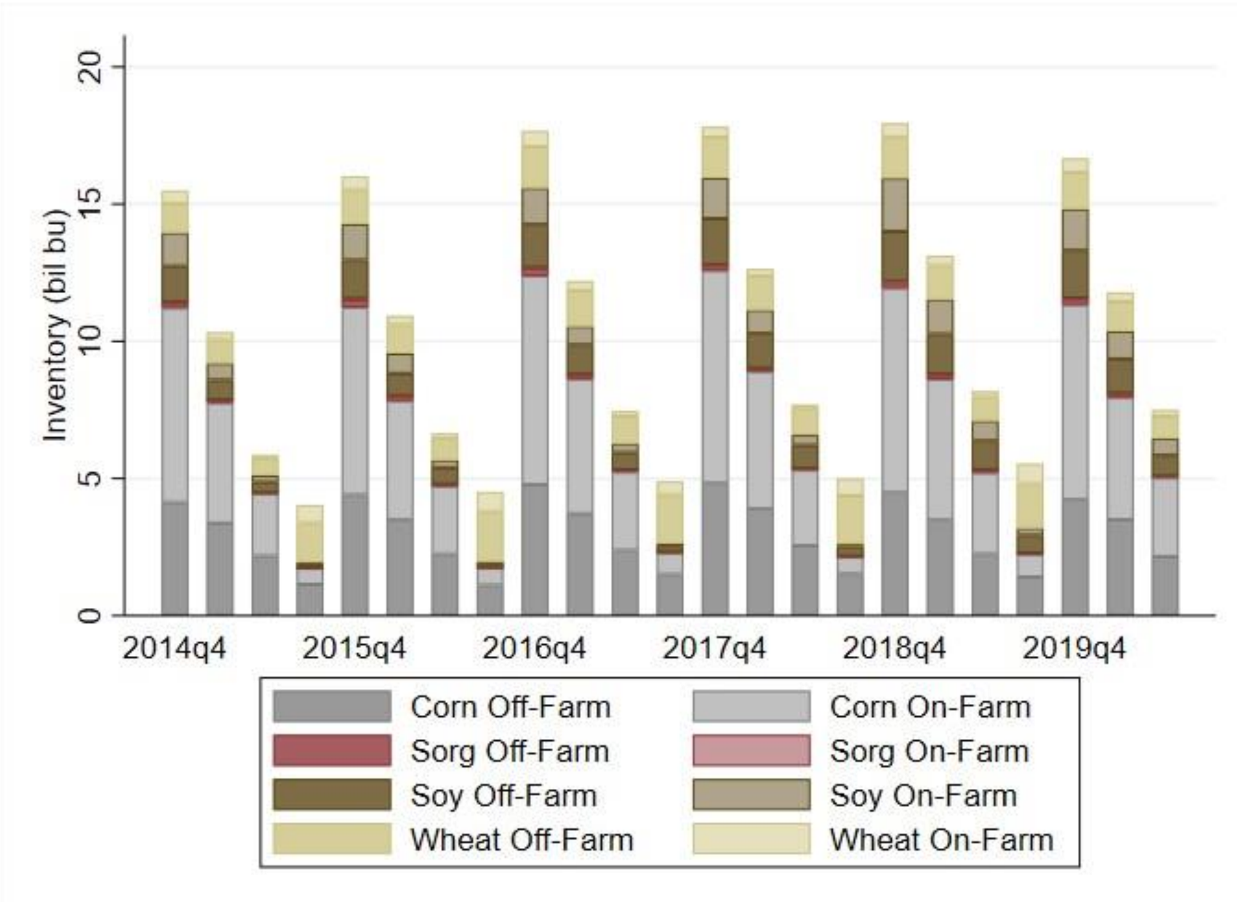
4.2 Summary Statistics

Using the panel dataset described above, this section will look at how these variables vary across the five dimensions: state, commodity, marketing year, quarter, and storage location. The summary statistics that are produced only include the data that is used in the empirical model. These data are limited by the inventory data and more specifically on-farm inventory. This dataset includes 2,388 observations for off-farm inventories which spans 37 states. For on-farm inventories, the set includes 1,236 observations that spans 24 states. Summary statistics tables and correlation matrix can be found in Appendix A.

Inventory & Production

Figure 4 displays how total United States inventories vary across commodity, quarter, and storage location. Inventory levels for each crop are typically the highest after harvest and decrease throughout the marketing year. Given the marketing years explained earlier, for the fall harvest crops the 4th quarter has the highest inventory levels. Stocks for summer harvest crops peaks in the 3rd quarter. Producers can only store the amount they produce and the amount they carry over from the previous crop year. This leads to strong correlation between the size of each year's production and inventories at the start of the marketing year. For corn, the correlation between on-farm inventories and production is 0.85. The other commodities are all above 0.4 as well. The correlation matrix for all commodities is included in table A-2 of the appendix.

Figure 4: Commodity, Time, and Storage Location of US Grain Stocks (2014q4-2020q2)



Notes: The National estimates provided through the *Grain Stocks* reports are used to create this graphic.

Due to this high correlation, the summary statistics for production and inventories for each commodity are expressed as a proportion. This proportion is calculated by taking the inventory levels in each quarter divided by the marketing year production for that commodity. This also allows for comparisons across commodities. The full summary statistics of the on-farm inventories and production are included in table A-3 of the appendix.

For the fall harvest crops, corn is typically the commodity that has the largest percentage stored on-farm at harvest time compared to their production. Corn averages about 52% of their production stored on-farm at harvest time compared to soybeans that average 37%. All three commodities show a low average for the percent stored on-farm at the end of the marketing year. This means that for these commodities it is not typical to carry over inventories into the next marketing year. Figure 4 shows this storage seasonality by displaying the draw down in stocks from quarter 4 to quarter 3 of that marketing year. For off-farm inventories, all three commodities only average 40% or less of their production stored off-farm at harvest time.

For wheat, the average amount of annual production stored on-farm across all states is 25% at harvest. This is lower than corn and soybean crops. Wheat also displays the largest percentage stored at the end of the marketing year at an average of 6.4%. For off-farm inventories, wheat averages 125% of the marketing years' production to be stored at harvest time. This is due to the higher carryovers from one marketing year to the next; this may be due the presence of larger price spreads in the wheat futures market relative to other crops.

MFP Payments

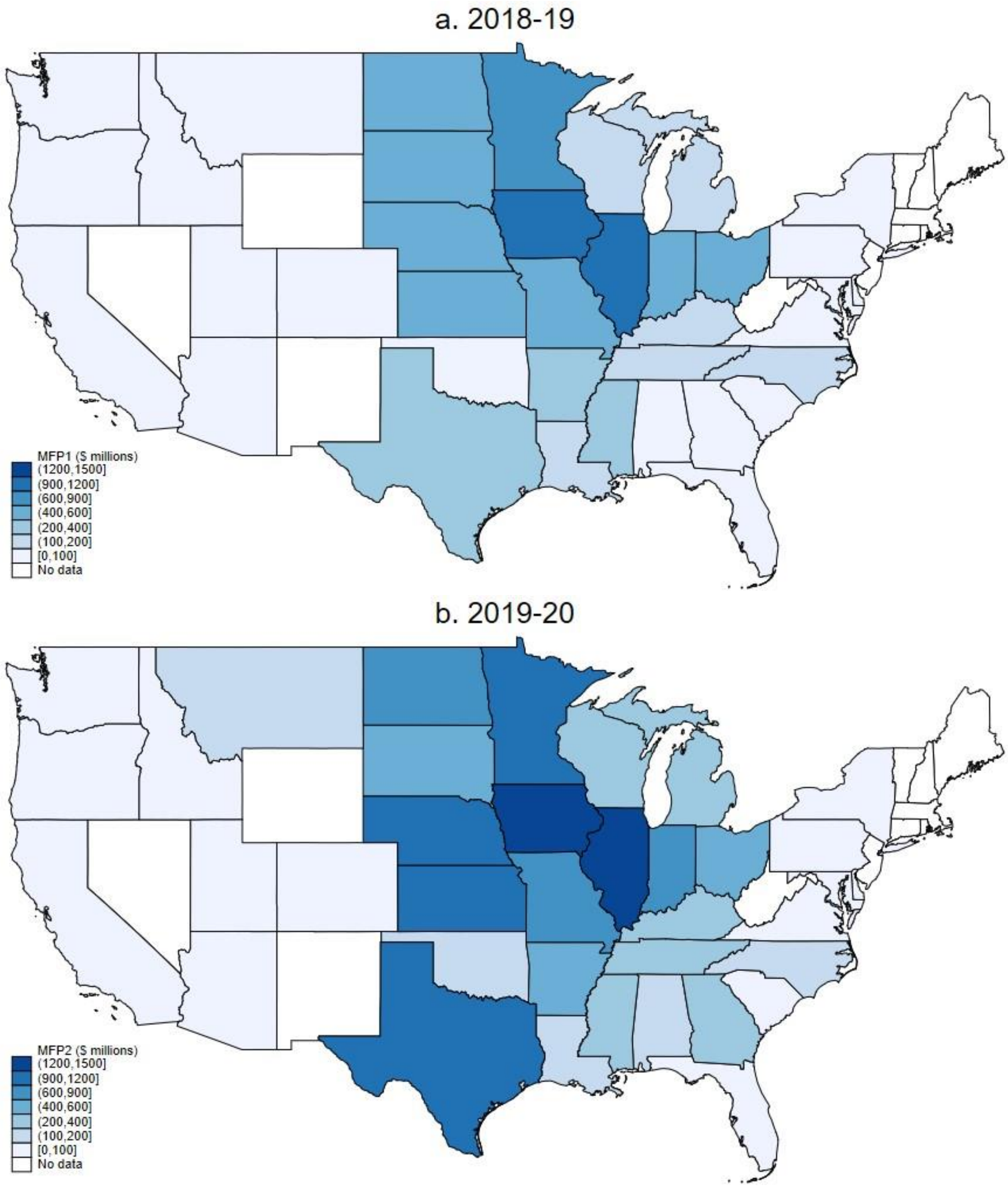
MFP payments vary across states, commodity, and marketing year. Due to the difference in how the payments were calculated and what commodities were included, the two rounds of MFP will be analyzed separately. MFP1 is defined as the payments that were distributed during the 2018 marketing year, while MFP2 is the 2019 marketing year payments. While we have MFP data for all states, these results are limited to those states where off-farm inventories are observed. MFP1 and MFP2 summary statistics can be found in tables A-4 and A-5, respectively.

Figure 5 displays the total MFP payments that were given out to non-specialty crops. This graphic provides a visual of which states are used in this analysis. The white states are the ones that off-farm inventories are not accounted for. Another variation these maps display is that in 2019 more money was allocated to this program. Therefore, most states saw a larger MFP payment overall in 2019. The states in the Midwest saw the largest payments in both years. Part of this is due to higher production of these commodities not that they were impacted by the trade war more than another state.

MFP1 payments focused on soybeans as the main commodity that was targeted with the trade war with China. This explains why soybeans' range of payments were 166-1067 million dollars which is significantly higher than the other commodities. For corn, the payments only ranged 0.81-24 million dollars. The amount of MFP1 payments a state received depended on the planted acres for that specific commodity. Therefore, states will receive a higher payment for a specific commodity if they plant more of that commodity. By looking at the average across all states, we get a sense of what the payments looked like for each commodity. The averages for corn, sorghum, soybeans, and wheat are 7.8, 53, 498, and 11.4 million dollars, respectively. This makes it clear that soybeans got the majority of the MFP1 payments.

MFP2 payments are calculated differently as explained in the background section. The USDA did try to compensate those other commodities that were impacted through the trade war not through loss of exports, but by the decrease in commodity prices. Therefore, the payments are more evenly distributed across the commodities. Those states that plant more acres to all the commodities will receive a higher total MFP payment. The MFP2 averages for corn, sorghum, soybeans, and wheat are 283, 85, 323, and 77.5 million dollars, respectively. The range of soybean payments decreased significantly to 77-697 million dollars. For corn the payment range increased to 34-877 million dollars. Wheat received higher payments in 2019 as well. The max wheat payment was 352 million dollars across 20 states.

Figure 5: Cross-Sectional and Time Variation of Non-Specialty MFP Payments

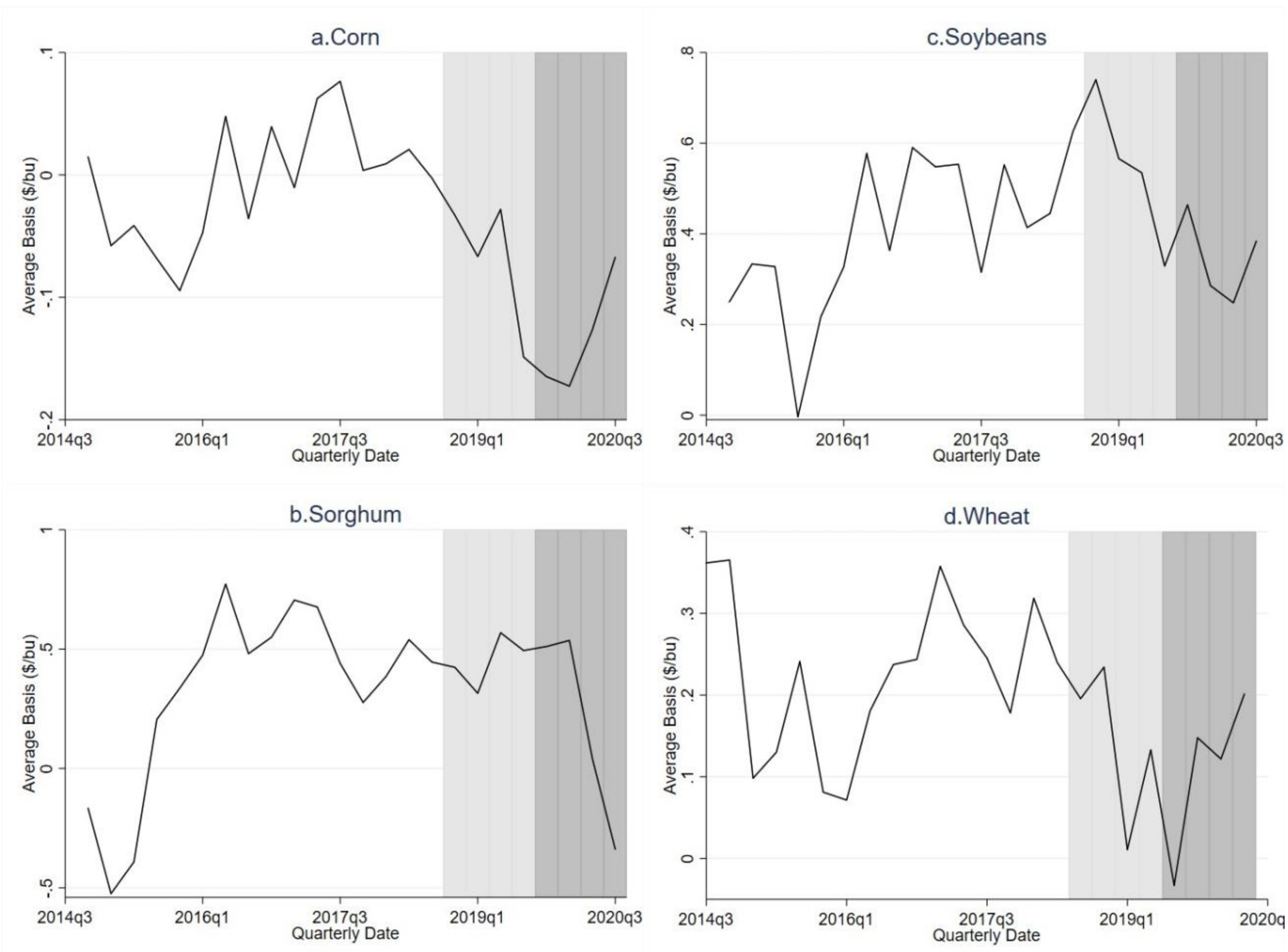


Notes: The scales are the same for both years. States included are those that have off-farm stocks reported for at least one commodity. Non-specialty crop payments include corn, soybeans, sorghum, wheat, cotton, barley, and more

Trade War Covariates

Each commodity and state were impacted by the trade war differently. To get a sense of how each state and commodity was impacted by the trade war, we look at what happened to basis over time and used a state-level export estimation. A futures-cash basis is created using the cash and futures dataset. Typically, the futures price is larger than the cash price for these commodities. This means that the basis measured in this study will be weaker when the basis value is more positive. Basis provides variation at a state-commodity-marketing year-quarter level.

Figure 6: Average Variation in Basis for Each Commodity over Time



Notes: These graphics were calculated with using a simple average across all states. The shaded regions demonstrate the 2018-19 and 2019-20 marketing years.

Figure 6 displays the average variation in basis for each commodity over time. The shaded regions are the two marketing years and the periods that each MFP payment is applied in the model. A couple quarters leading up to the 2018-19 marketing year demonstrates what happened to the price of storage during the start of the trade war. Soybeans saw the impact of the trade war more seeing as basis weakened during the start of 2018 due to loss of exports. Corn saw smaller impact leading up to the 3rd quarter of 2018. Wheat basis improved while sorghum basis remained steady. By using a state-level basis variable, we can capture how basis was impacted based on various market conditions, like export dependence, that are specific to each state and commodity.

Another alternative measure of export dependence relevant to the potential impact of the trade war on grain inventory is a state-level commodity export variable. The USDA Economic Research Service estimates state-level export value data by using U.S. farm-cash-receipts data. Due to the limitations of being able to trace the commodity back to the farm-level, total US exports are allocated to states based on production value share (ERS, 2020). These data are published in million dollars and includes our four commodities and more. Most of the variation in this variable is attributed to changes in US export values for each commodity or state-level production shares.

The summary statistics above explain that this panel dataset has state, commodity, marketing year, quarter, and storage location dimensions. Variation across some of these dimensions should not be attributed to MFP. For example, inventories will be larger in states with greater production. To construct an empirical model to estimate the policy impacts that MFP had on on-farm grain storage and producers' marketing decisions, a fixed effects regression model will be used to adjust for differences in inventories along some of these dimensions.

5 Methodology

This section lays out the empirical fixed effects model used to estimate the policy impact (MFP) on the supply of grain inventories. The purpose of this model is to isolate the variation in MFP that is uncorrelated with the market shock caused by the trade war. This allows the model to measure the change in inventories in those states that received relatively more in MFP compared to those receive less. To do so, this study exploits the fact that MFP payment calculations for a given commodity were the same across all farms, while the effect of the trade war on commodity prices varied across space.

5.1 Fixed Effects Model (FE)

Our econometric model is analogous to a difference-in-difference (DiD) model where each state and commodity has differing exposure level to the treatment model. A DiD requires a particular structure for the data to be analyzed: two time periods (pre & post) and a treatment variable with a control group (Kropko & Kubinec, 2020). Our data is structured without a control group as all states were eligible and received an MFP payment. While a true DiD is not able to be used, a fixed effects model will analyze the variation of MFP exposure within each state over time. This will allow the effect of MFP to be compared based on those states that receive relatively more verses those that receive relatively less. This allows units to act as their own control (Strumpf et. al, 2017). Treated observations in this situation are all states with on-farm inventories in the 2018-19 and 2019-20 marketing years. The pre-periods will provide a control for how inventories in each state were impacted over time before the implementation of MFP payments.

Due to the nature of the variation in the data, a fixed effects model with multiple dimensions is created. By adding fixed effects to the model, it allows for time, state, and seasonalinvariant confounders to be removed or differenced out. The purpose of including marketing year and state fixed effects is to remove common shocks in storage behavior across states and over time. These models also include a fixed effect for commodity by quarter. This is to account for the differences in storage behavior across crops, including differences in storage seasonality.

Other fixed effects, such as marketing year by quarter by commodity, could have been used in this model as well. The reason the three we chose are included is due the amount of explanatory power that it provides for the model. The three chosen explain over 80% of the variation in inventory levels. Adding additional fixed effects will not control for too much more variation due to a lot of the variation already being captured. Another reason is by adding a fixed effect across commodity by marketing year would likely capture some of the variation that the MFP payments would be explaining as they were assigned at a commodity-marketing year level. The main goal for these fixed effects is to alleviate the bias in the impact MFP payments had on on-farm inventories by reducing the variation that is related to how these payments were calculated

Our model assumes when these MFP payments impact a farmers' willingness to store. As explained earlier, the MFP payments are allocated to each quarter of the respective marketing year. This aligns with the timeline that farmers received their payments and would be able to use them. The MFP1 payments were both announced and paid out during the first two quarters of the fall-harvest crops 2018-19 marketing year. For MFP2 the announcement happened at the end of quarter 2 of 2019, but the payments were not dispersed until the beginning of September and divided into three payments until February. By matching it this way, it also aligns with the start of the farmers' storage decisions and when they would be impacted by the decrease in opportunity cost of storage.

Since this modeling is analogous to a DiD event study, the parallel trend assumption must also hold. This assumption means that unobserved characteristics affecting program participation does not vary over time with treatment status (Khandker et. al, 2010). In other words, there is not a statistically significant inventory response to the MFP payments prior to the program. We believe this assumption holds based on how we time our impact of the MFP payments. This assumption is tested using a distributed log model and graphical representation.

Model Specification

The model specification for these regressions model is an inverse hyperbolic sine transformation (IHS) on both sides of the equation. An accent (~) over the variable will denote those variables that have been transformed using the inverse hyperbolic sine transformation.

We chose a log-based model to reduce skewness and narrow ranges of our variables that have skewed distributions (Aihounton & Henningsen, 2020). An IHS-transformation approximates the natural logarithm of that variable but allows for retaining zero-valued observations. Due to the MFP data including zeros in the pre-periods and the basis variable having negative variables, a typical log transformation is not applicable.

One of the major drawbacks to the IHS transformation is that the estimated coefficients only provide an estimated elasticity. To obtain a more stable elasticity the variables must have a large enough average values for x and y (Bellemare & Wichman, 2019). For this purpose, the data are in dollars or bushels. This transformation also reduces the influence of outliers in a dataset. Bellemare & Wichman, 2019 express that this transformation on a control variable does not impact the casual interpretation of a treatment variable.

In each of the regression models below, the standard errors are clustered by marketing year by commodity. MFP assignments were not independently assigned at each level of our panel data set. The Market Facilitation Program payments were jointly assigned based on the marketing year announced and the commodity that was planted. Since our treatment variable assignment mechanism is clustered at this level it provides a justification to cluster all observations at this level (Abadie et. al, 2017). While we control for some of this variation in our fixed effects, it is not likely that our estimation is homogenous. Therefore, this leaves an opening to cluster the standard errors. We cluster to control for those observations within each marketing by commodity that is correlated in some unknown way. The observations in this problem include inventories in each state, quarter, and storage location. Each one of these dimensions is included in our FE model, but there is some unknown variation that does not affect these observations individually.

We analyze what impact this policy had on on-farm inventory levels in the 2018-19 and 2019-20 marketing years. The effect of interest is identified by differences in the change in inventory over time between states that received proportionally more MFP dollars relative to those that received proportionally less. Equation 3 shows the baseline regression model. β_1, the coefficient on the treatment variable MFP_Comm_{icqt}, is the estimator of interest.

Equation 3: Baseline Regression Model

$$\tilde{Y}_{icfqt} = \beta_0 + \beta_1\, \widetilde{MFP_{Comm}}_{icqt} + \beta_2\, \widetilde{MFP_{Other}}_{icqt} + \delta \tilde{X}_{icqt} + \alpha_i + \gamma_t + \eta_{cq} + \varepsilon_{icqt}$$

for i=state, c=commodity, f=location, q=quarter, and t=marketing year.

In this model the fixed effects are, α_i is a state-specific fixed effect, γ_t is a marketing year fixed effect, and η_{cq} is a commodity by quarter fixed effect. Y_{icfqt} denotes the amount stored in inventory for that state-commodity—location-quarter-marketing year. The baseline model will be estimated only using on-farm inventories (f=1). X_{icqt} is a set of covariates that account for possible confounders in state ***i*** in year ***t*** in quarter ***q*** and commodity ***c***. This set of covariates includes production (X_{ict}), futures-cash basis (X_{icqt}), and a state-level commodity export (X_{ict}).

These variables are those that are proposed to control for confounding inventory demand shifters. Different variations of this model will be ran with these different covariates and fixed effects with the goal of alleviating the bias on the impact of MFP from a change in the demand for inventories. Futures-cash basis will be able to capture the difference in state-commodity market impacts. This allows for this model to capture the variation in basis based on how dependent that commodity and state is on exports, changes in production, and other local demand factors for each commodity.

The treatment variable, MFP_Comm_{icqt} is the continuous measure of how much state ***i*** received in MFP for commodity ***c*** in quarter ***q*** and year ***t***. The MFP_Other_{icqt} variable is the amount of MFP given to other non-specialty crops in state-quarter-marketing year. It is calculated by taking the total non-specialty MFP payment and subtracting the commodity payment (MFP_Comm_{icqt}). Since payments are fungible, a farmer could have received payment for one commodity but decided to store a different commodity. This variable is added to control for the impact to state inventories based on what the state received in MFP for other commodities.

5.2 Empirical Tests

The following section will explain how we test two of the main assumptions; parallel trends and impact to on-farm inventories.

Testing the Parallel Trends Assumption

For the estimates in our baseline analysis to be causal, there must not be any anticipation in inventory changes prior to the implementation of the Market Facilitation Program. We also want to ensure there are no pre-existing reasons that inventories are changing over time across states. The parallel trends assumption states that there should be no statistically significant inventory response prior to the MFP payments. To analyze the parallel trends assumption, we must define the effect window, or period where MFP could cause a dynamic change to inventories. We use the 2014-15 to 2019-20 effect window to test this assumption. The effect window for this model includes a finite number of leads and lags, $\underline{j} = -4$ to $\overline{j} = 1$. The effect outside this window is assumed to stay constant. The parallel trends analysis will follow Schmidheiny and Siegloch's (2020) multiple events of different intensities distributed-lag model methods. For state ***i*** and commodity ***c***, the events and intensities are defined as $E1_{i,\,c,\,2018}$ and $E2_{i,\,c,\,2019}$; there are no events in the other years. $E1_{i,\,c,\,2018}$ is defined as the amount of MFP in state ***i*** for commodity ***j*** in the 2018-19 marketing year (t). $E2_{i,\,c,\,2019}$ is defined as the amount of MFP in 2019-20 for the state-commodity combination. Table 1 shows the distributed-lag model in levels, $x_{ict} = x_{ict} + \Delta x_{i,c,t-1}$ with initial value $x_{i,c,t-\overline{j}} = 0$.

Table 1: Parallel Trends Event Matrix

t	$x_{i,c,t+3}$	$x_{i,c,t+2}$	$x_{i,c,t+1}$	$x_{i,c,t}$	$x_{i,c,t-1}$
2014-15	0	0	0	0	0
2015-16	E1	0	0	0	0
2016-17	E1+E2	E1	0	0	0
2017-18	E1+E2	E1+E2	E1	0	0
2018-19	E1+E2	E1+E2	E1+E2	E1	0
2019-20	E1+E2	E1+E2	E1+E2	E1+E2	E1

Notes: E1 demonstrates the amount paid out for MFP1 and E1+E2 will be the total payment amount of both MFP1 and MFP2. Follows example A.2 of Schmidheiny & Siegloch (2020).

Using equation 3, a distributed-lag model is designed with these leads and lags replacing the MFP_Comm_{icqt} variable, as seen in equation 4.

Equation 4: Distributed Lag Model

$$\tilde{Y}_{icqt} = \sum_{j=-\underline{j}+1}^{\bar{j}} \gamma_j x_{i,c,t-j} + \beta_0 + \beta_1 \widetilde{MFP\_Other}_{icqt} + \delta \tilde{X}_{icqt} + \alpha_i + \gamma_t + \eta_{cq} + \varepsilon_{icqt}$$

All the other controls and fixed effects remain the same as equation 3. The purpose of this analysis will be to make sure the coefficients before $x_{i,c,t}$ are insignificant. This will provide evidence that the pre-trends assumption holds, and the rest of the results are supported. MFP_Other variable was not lagged in this model, just the MFP payments paid out to specific commodity.

Falsification Test

To assess our main assumption that only on-farm inventories were impacted by MFP payments, this study runs a falsification test. This falsification test will be using the baseline model (equation 3) but estimate it with off-farm inventories (f=0) as the outcome of interest. If MFP only affected on-farm inventories (i.e. other firms in a given state did not respond to these payments), then the β_1 and β_2 coefficients should be insignificant. Statistically insignificant coefficient estimates, support that the idea that on-farm inventories are relatively impacted more than off-farm inventories and the effect we estimate in equation 3 is more likely to be related to a shift in willingness to store caused by the receipt of MFP payments

This test could also have been ran jointly with on-farm inventories by using interaction effects with a dummy variable for storage location. By running the analysis just with off-farm inventories, we allow all the variables and fixed effects to become off-farm specific. This means all the coefficients will be different since production, basis, and fixed effects can impact off-farm inventories differently than on-farm. The comparison between the baseline model and the falsification test will solidify our assumption that on-farm inventories were impacted more and provide support for the theory behind our baseline model.

6 Results

The empirical results and tests for both models are presented in this section. This study finds that MFP payments had a significant impact on grain storage by US farmers. Due to data limitations, this study includes potential alternatives for further research opportunities.

6.1 Model 1: Baseline Results

Using the baseline regression, or equation 3, this study finds a positive and significant effect of MFP on on-farm grain storage. Equation 3 was ran with a progression of additional fixed effects and control variables. While we emphasize the estimation of the coefficients on the MFP variables (β_1, β_2), considering the differences in the explanatory power of the other regression is important to understanding the various cross-sectional differences that are distributed in the dataset. Most of the variation in our models come from the additional fixed effects and controls. The results are displayed in table 2. Column (A) shows results of regressing on-farm inventories on only the MFP variables. This displays the amount of variation in on-farm inventories as a result of more dollars of MFP. While this coefficient is insignificant, it explains that the MFP variables hold little overall explanatory power on grain stocks.

Table 2, column (B) includes both MFP variables and adds a marketing year fixed effect. The results for this model are significant, but still low of explanatory power. Looking at column (C) and (D), we notice that as more fixed effects are added the marginal effect of MFP on inventory decreases and the explanatory power increases. Column (C) adds the state fixed effects. Just by adding a fixed effect for each state increases the explanatory power by 38% and the marginal effect of MFP decreases by 0.29. Column (D) displays that MFP variables and all three fixed effects explains about 87% of the variation in on-farm inventories.

Due to the events of the trade war during the same period, we expect these coefficients (Column (D)) to still be biased. This is due to the impact that the trade war had on the increase in the demand for grain storage. By adding the additional regressors to control for changes in demand for inventories, we try to alleviate this bias. Columns (E) and (F) display the marginal effect of MFP on on-farm inventories with adding the additional regressors. These additional regressors increase the explanatory power by about 8%. Both of these were ran with production as a control regressor. Column (E) and (F) are ran using the two different options for the covariate to control for state-level export dependence. Column (E) uses futures-cash basis and column (F) includes the state-level export variable. The difference in explanatory power between the two models is less than one-percentage. This tells us that the two variables are likely controlling for similar variation in on-farm inventories.

The state export variable is not a great measure for state export dependence due to the fact that it is difficult to track exports back to their original source of production (ERS, 2020). The USDA-ERS estimates this variable based on the value of US exports allocated to each state based on their production. This variable also was only at a state-marketing year-commodity level, whereas basis adds a quarterly variation to exploit. While the futures-cash basis provides fewer observations due to the Bloomberg terminal not including cash prices for a few states, it provides a better control for changes in the demand for inventories. For these reasons, column (E) is our preferred specification of our baseline model with the futures-cash basis control variable.

The total impact that the MFP payments had on on-farm grain storage is expressed as the combined MFP coefficients. Column (E) explains that with a 10% increase in MFP payments, US on-farm grain inventories would have increased by 1.28%, holding all else constant. To extrapolate out this effect, we look at the difference in MFP dollars given between MFP1 and MFP2. MFP2 paid out 6 billion more dollars of MFP or a 70% increase compared to MFP1. Based on this our estimator would explain that we would see an almost 9% increase in on-farm inventories in the 2019-20 marketing year compared to 2018-19 holding all else constant.

Table 2: Baseline Regression Results

	Dependent Variable: IHS(On-farm Inventory)					
	(A)	(B)	(C)	(D)	(E)	(F)
MFP_Comm	0.280	0.654*	0.361*	0.300***	0.124***	0.123***
	(0.142)	(0.234)	(0.441)	(0.059)	(0.028)	(0.022)
MFP_Other	-0.245	0.089	-0.013	-0.043	0.004	-0.017
	(0.137)	(0.169)	(0.153)	(0.037)	(0.012)	(0.016)
Production					1.144***	0.910***
					(0.053)	(0.049)
Basis					-0.132	
					(1.04)	
Exports						0.373***
						(0.054)
R^2	0.036	0.083	0.441	0.868	0.951	0.955
N	1236	1236	1236	1236	1212	1236
Marketing Year FEs		x	x	x	x	x
State FEs			x	x	x	x
Comm x Quarter FEs				x	x	x

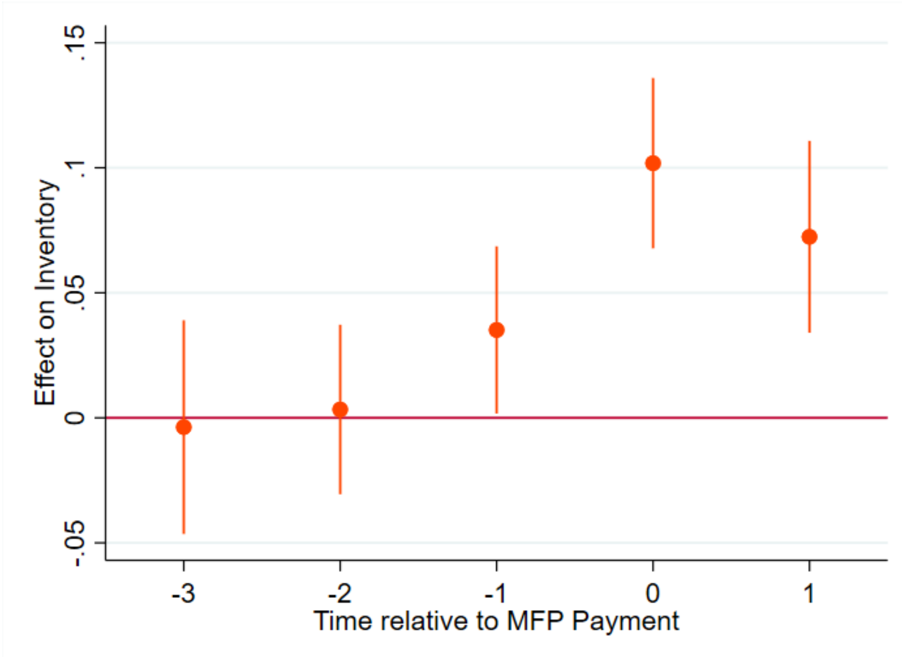
Notes: all continuous regressors transformed using inverse hyperbolic sine. Heteroskedasticity-robust standard errors clustered at the (Marketing Year x Commodity) are below estimates. *=90% **=95% ***=99%

Parallel Trends Test

Figure 7 displays the inventory effects of the MFP payments by plotting the distributed lag estimates from equation 4. The distributed lag model estimates show that the 2015-16 and 2016-17 marketing year leads are insignificant, but the 2017-18 marketing year lead is significant at a 95% confidence level. This is likely due to there being some anticipation of these payments in the quarters leading up to the 2018-19 marketing year. Hence, the results of the event study confirmed that an increase in MFP payment implies an increase in on-farm inventory. Including the three leads to the study, we find that there is a flat pre-trend with some slight anticipation leading up the 2018-19 marketing year. The 2018-19 marketing year and the 2019-20 marketing year both had significant coefficients at a 99% confidence level. This provides evidence that the impact of MFP should be applied to these two marketing years. The regression results for this test are displayed in table A-6 in the appendix.

This test also allows us to see where the majority of the impact of MFP might have happened. This figure portrays the largest part of the impact comes during the 2018-19 marketing year with a decrease going into the 2019-20 marketing year. Based on the mechanism of impact, we believe that there should be more of an impact in the 2019-20 marketing years due to the larger payments given out during that marketing year. To confirm if this is true, we would need to have data for the 2020-21 marketing year to complete the last full lag according to Schmidheiny and Siegloch, 2020.

Figure 7: Parallel Trends Analysis



Notes: Time expressed in years relative to both MFP1 and MFP2 payment amounts following Schmidheiny and Siegloch (2020). i.e. For 2017-18 marketing year, t=-1 MFP level is the MFP1 payment amount ant t=-2 is the MFP1+MFP2 payment amount.

6.2 Model 2: Falsification Test

Model 1 is only ran using on-farm inventories. The reasoning behind this is due to the intuition that these payments went directly to producers and impacted the farmer storage supply. To check our assumption that MFP only impacted on-farm inventories, model 2 is ran with just off-farm inventories. Model 2 provides support to our expectations that on-farm inventories should increase more relative to off-farm inventories. This model is ran using the basis and production covariates along with the coefficient of interests (equation 3). The results for this model are displayed in table 3.

The coefficients of interest (β_1 & β_2) are both insignificant with p-values of 0.285 and 0.703 respectively. By comparing these results to those in model 1 (Table 1), it is clear the amount that is produced places a larger role in on-farm inventories than off-farm. This is one of the benefits of running the model separately from on-farm inventories is to allow for the production and basis coefficients to be off-farm specific. We did check this assumption by jointly running the regression using interaction terms with location and found similar findings. They both provide evidence that on-farm inventories were impacted relatively more than off-farm inventories. A full table of results is in table A-7 of the appendix.

Table 3: Falsification Test Results

Dependent Variable: IHS(Off-Farm Inventory)	
MFP_Comm	0.0277
	(0.0254)
MFP_Other	0.0086
	(0.0223)
Production	0.8325***
	(0.0238)
Basis	-0.0124
	(0.0645)
R^2	0.9122
N	2312

Notes: All continuous regressors transformed using inverse hyperbolic sine. Heteroskedasticity-robust standard errors are below estimates and clustered at the (Marketing Year x Commodity). Full results can be found in table A-7 of the Appendix. ***=90% **=95% ***=99%**

6.3 Implications and Further Research

The dataset presents challenges for further analysis to increase the validity of these estimates. Due to the data being aggregated to a state level, we do not have a clear control group. This makes it difficult to extrapolate the estimated effect to a case where there was no MFP. The MFP effect is also averaged across states, time, and commodity which also poses its own limitation. This makes it so the effect of MFP is similar across time and commodities. Having farm-level data would provide a control group or a no-MFP scenario and provide more information on how and when farmers reacted to receiving these payments.

Another option to get a control group is to create a binary MFP treatment variable with those states that received a high amount of MFP as treated and the others as the control. This presents its own difficulties of defining what a high-level of MFP state would be. Creating a binary treatment variable will also take away some of the variation that comes with having a continuous treatment variable.

The main task of our covariates is to isolate the variation in MFP that is uncorrelated with market shock caused by trade war. Having a better measure of how each state was impacted by the trade war would also increase the validity of these estimates. Our state-level export variable could be improved if it was a better representation of the commodity flow for exports for each state. This type of unaggregated export data are not readily available. The basis variable that has been used in this study is also not a perfect control. Basis not only depends on the time interval of our cash and futures data, but also on location, quality differences, and delivery conditions (Tomek & Kaiser, 2014). By averaging the basis variable to a state-level, we remove these different dimensions. These dimensions would assist in providing more detail on how each producer reacted based on the basis values in their area.

Overall, these results align with the theory of grain storage. They show that on-farm storage was impacted by the increase of these ad hoc payments. By knowing some of these limitations of the data, we can improve the estimates with future research.

7 Conclusions

This study looks at the potential impacts the Market Facilitation Program payments in 2018-19 and 2019-20 marketing years had on grain stocks. Our overview of the theory of storage explains that the main mechanism for this impact is through a lower opportunity cost of storage. This lower opportunity cost of storage incentivizes producers to store more of their grain. Combining the theory of storage with our empirical model, this study shows evidence that programs like MFP allow producers to "buy time" and store more grain until markets are more desirable.

Our empirical model provides support to our assumptions and the mechanism of impact. Those states that received more in MFP payments ended up storing more relative to those states that received relatively less. Between MFP1 and MFP2, there was a 70% increase in Market Facilitation Program payments. Based on this the baseline results explain that in 2019-20, we would have seen about a 9% increase in on-farm inventories compared to 2018-19 marketing year. Our falsification test on off-farm inventories provides us further evidence that these payments impacted on-farm storage only, corroborating the idea that payments affected the supply rather than just the demand for storage. These higher inventories could lead to lower prices or provide less opportunities for producers to capture higher prices later such as those offered by carry levels in futures markets.

The nature of the data makes it challenging to extrapolate the potential impact of MFP and estimate the aggregate impact of MFP on US grain storage. Specifically, we do not observe a set of "pure control" states that did not receive MFP payments. This study suggests some supplementary analysis that can be conducted to further explore the potential impacts and help provide an estimate of MFP relative to non-MFP scenarios. Further research should be conducted to add more post-treatment time periods to allow for additional analysis on impacts past the 2019-20 marketing year. To increase the validity of our analysis, creating a binary treatment variable will allow for a true difference-in-difference model estimation. Additionally, one could use similar methods to test whether other ad hoc government payments, such as the recent Coronavirus Food Assistance Program payments, have similar effects on grain inventories. Similar outcomes in a different context based on our mechanism of impact would provide further support for our results.

Despite some of the empirical challenges, this study provides a baseline analysis of how policies could potentially impact grain storage. The results of this study are beneficial to policy analysts to look at how policies that increase access to financial capital could impact farmers' marketing and storage decisions. If there are policies that are incentivizing grain producers to store more, that could impact the futures and cash markets for grain. With higher inventories, the financial market is lower and more stable than in years with lower inventories. There are plenty of times that policies have unintentional effects on farmers' decisions. Its important to analyze what happens to inventories due to these policies as they could impact the overall financial market for grain producers.

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Appendix A - Supplementary Analysis

Summary Statistics

Table A-1: Dominant Type of Wheat Grown in each State

Hard Red Winter	Soft Red Winter	Hard Red Spring	Soft White
Arizona	Alabama	Minnesota	Idaho
California	Arkansas	North Dakota	Nevada
Colorado	Delaware		Oregon
Kansas	Florida		Washington
Montana	Georgia		
Nebraska	Indiana		
New Mexico	Kentucky		
Oklahoma	Louisiana		
South Dakota	Maryland		
Texas	Michigan		
Utah	Mississippi		
West Virginia	Missouri		
Wyoming	New Jersey		
	New York		
	North Carolina		
	Ohio		
	Pennsylvania		
	South Carolina		
	Tennessee		
	Virginia		
	Wisconsin		

Notes: These were calculated using 5-year production averages from USDA-NASS (2016-2020)

Table A-2: Inventory to Production Correlation Matrix for each Commodity

Correlation in On-farm Inventory to Production for US

Commodity	Correlation
Corn	0.85
Sorghum	0.67
Soybeans	0.44
Wheat	0.72

Notes: This is only on-farm inventories correlation with production

Table A-3: Inventory/Production Summary Statistics

Proportion of Inventories to Production Across State for Each Commodity and Quarter (%)						
Commodity	Quarter	Obs	Mean	Std. Dev	Min	Max
Corn	1	96	32.21	10.01	10.42	53.77
	2	96	18.08	7.77	3.44	40.66
	3	96	5.23	3.29	0.97	21.58
	4	96	52.20	13.80	20.24	89.76
Sorghum	1	22	5.13	3.91	0.66	14.29
	2	22	2.35	2.26	0.07	8.19
	3	22	1.27	1.52	0.03	4.88
	4	23	15.61	15.62	2.01	69.08
Soybeans	1	72	21.54	8.09	8.31	44.02
	2	72	11.25	6.28	2.09	28.53
	3	72	2.99	2.35	0.19	10.35
	4	72	36.59	10.43	16.82	55.44
Wheat	1	119	11.47	13.30	0.15	44.17
	2	116	6.39	8.75	0.04	33.83
	3	120	24.74	23.91	1.49	93.28
	4	120	17.78	19.94	0.46	72.17

Notes: These were calculated dividing inventory for each quarter and commodity by the production for that marketing year. Only includes on-farm inventories.

Table A-4: 2018 MFP Summary Statistics by Commodity

Summary Statistics for MFP1 (Million dollars)					
Commodity	Obs.	Means	Std. Dev	Min	Max
Corn	16	7.80	7.29	0.81	24.05
Sorghum	4	52.93	73.86	1.73	160.69
Soybeans	12	498.09	267.71	166.59	1,066.76
Wheat	20	11.35	13.29	0.76	54.10

Notes: Only includes those states that off-farm inventories are included in our analysis

Table A-5: 2019 MFP Summary Statistics by Commodity

Summary Statistics for MFP2 (Million dollars)					
Commodity	Obs.	Means	Std. Dev	Min	Max
Corn	16	282.99	254.89	33.78	877.29
Sorghum	3	84.94	70.37	4.11	132.52
Soybeans	12	322.61	185.31	76.66	697.40
Wheat	20	77.53	99.14	4.79	351.88

Notes: Only includes those states that off-farm inventories are included in our analysis

Supplementary Regression Results

Table A-6: Parallel Trends Regression Results

Variable	Coefficient	Robust Standard Error	P-value
2015 Lead	-0.0037	0.022	0.865
2016 Lead	0.0033	0.017	0.847
2017 Lead	0.0351**	0.017	0.039
2018	0.1018***	0.017	0.000
2019 Lag	0.0724***	0.020	0.000
MFP_Other	-0.0177	0.014	0.220
Production	1.1222***	0.035	0.000
Basis	-0.136**	0.065	0.037
Constant	-5.693***	0.579	0.000
R-squared	0.9518		
N observations	1212		

Notes: all continuous regressors transformed using inverse hyperbolic sine. Heteroskedasticity-robust standard errors clustered at the (Marketing Year x Commodity) are below estimates. *=90% **=95% ***=99%

Table A-7: Full Falsification Regression Results

Variable	Coefficient	Robust Standard Error	P-value
MFP_Comm	0.0278	0.0254	0.285
MFP_Other	0.0087	0.0224	0.703
Production	0.8325***	0.0238	0.000
Basis	-0.0124	0.0650	0.850
Constant	1.523***	0.4882	0.005
R-squared	0.9122		
N observations	2312		

Notes: all continuous regressors transformed using inverse hyperbolic sine. Heteroskedasticity-robust standard errors clustered at the (Marketing Year x Commodity) are below estimates. *=90% **=95% ***=99%