

Is there a racial gap in Market Facilitation Program payments and total government payments?

by

Ashling Mirjana Murphy

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Approved by:

Major Professor  
Dr. Nathan Hendricks

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## **Abstract**

In 2017, there was 32,910 Black or African American farms that were primarily located in the southeast and mid-Atlantic and had an average farm size of 125 acres. In comparison, 1,963,286 farms were White and had an average farm size of 431 acres (USDA NASS, 2017). In 2017, Black producers received \$59 million (0.7%) and White producers received \$8.9 billion (99%) of total government payments (USDA NASS, 2019). Black farms received 0.17 percent of the total share of Market Facilitation Program payments compared to White farms who received 99.18 percent of payments (Giri et al., 2022). Some policymakers have raised concerns about this apparent disparity in government payments between Black and White farms. However, no existing analysis explains the source of the racial gap. In this thesis, I conducted two sets of analysis using the micro-level Census of Agriculture data from 2017 to provide new insights on the racial gap. The first analysis examined the amount of payment from the 2018 Market Facilitation Program (MFP) that farms were eligible to receive and provided a decomposition to measure how much of the difference in eligible payments was due to differences in yield, acreage, and the share of crops produced. The second analysis utilized six regressions that estimated the average difference in total government payments in 2017 for Black farms compared to White farms. The regressions showed, on average, how much more or less money Black farms received when some agricultural factors were held constant. Findings from the first analysis concluded that conditional on a particular farm size, the 2018 MFP payment eligibility was larger for Black farms rather than White farms. But, because black farms tend to be smaller on average, the average MFP payment among Black farms was smaller than for White farms. Black farms were eligible for a smaller 2018 MFP payment than White farms mainly due to their farm size compared to their yields and crops they grew. The second analysis found that Black farms received on average about \$7,395 less in government

payments in 2017 compared to White farms. About twenty percent of this gap can be explained by differences in farm size. Even after controlling for farm size, county, the farm's location, gender of the farmer, and type of commodities produced, black farms still received on average \$4,959 less government payments.

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## **Dedication**

My thesis is dedicated to my Mom and Dad who have always motivated and supported me throughout my educational career. Thank you for always reminding me to aim high and be confident in myself!

## Chapter 1 - Introduction

One of the most memorable trade wars involving protectionist policies for U.S. agriculture was initiated by the Smoot-Hawley tariff of 1930. This act initiated a twenty percent tariff on imports of agricultural products and manufactured goods and added stress to America's already depressed economy. Many countries in North America and Europe protested this act and adopted their own retaliatory strategies which caused international trade and the world economy to weaken (Mitchener et al., 2021).

The most recent trade war began in 2018. On March 23, 2018, the United States imposed Section 232 tariffs on imports of steel and aluminum from our major trading partners in response to the Department of Commerce finding that importing these products threatened national security. This section is a component of the Trade Expansion Act of 1962 (Morgan et al., 2022). President Trump sanctioned a twenty-five percent tariff for countries that exported a total of \$10.2 billion of steel and a ten percent tariff for countries that exported \$7.7 billion of aluminum products to the United States (Bown & Kolb, 2018). On August 23, 2018, President Trump imposed a twenty-five percent tariff on a wide array of imports from China under Section 301 of the Trade Act of 1974 (Bown & Kolb, 2018). This was a result of an investigation led by U.S. Trade Representative Robert E. Lighthizer that found China used unfair trade practices related to technology transfer, intellectual property, and innovation (Bown & Kolb, 2018).

In response to the United States sanctioning Section 232 and 301 tariffs on their exports, Canada, China, the European Union, India, Mexico, and Turkey responded with retaliatory tariffs on a variety of U.S. goods. These included tariffs on \$30.4 billion of agricultural and food products. Although every retaliating country imposed a tariff on U.S. agricultural products, China's impact was the largest. China's sanctions accounted for approximately eighty percent of the retaliatory

tariffs against U.S. agricultural and food products (Grant et al., 2021). Ninety-eight percent of the 2017 U.S. agricultural exports to China were impacted (Grant et al., 2021). Retaliating countries targeted agricultural and food products because the United States is the largest agricultural exporter, the products can be imported from non-retaliatory countries and many influential political constituencies are in agricultural counties (Adjemian et al., 2021).

It is estimated that the U.S. endured a loss of more than \$27 billion in agricultural exports between mid-2018 to the end of 2019 (Morgan et al., 2022). The commodities that experienced the largest effects of trade destruction were soybeans and pork products because the Chinese tariff was set at twenty-five percent, and they were the top commodities exported to China (Carter & Steinbach, 2020). In response to the loss in agricultural exports, President Donald Trump authorized the USDA to implement the MFP and distributed \$23 billion dollars in 2018 and 2019. One critique of these payments has been the distribution method. Some have argued that it provided larger payments to Southern farms and relatively little payments went to socially disadvantaged and Black farms (Morgan et al., 2022).

The issue of racial discrimination with the government's ad-hoc payments through the Market Facilitation Program (MFP) and Coronavirus Food Assistance Program (CFAP) has raised a concern. MFP provided socially disadvantaged farmers with \$435.7 million which accounted for 1.89 percent of the total \$23 billion payment (Government Accountability Office, 2022). The Environmental Working Group found that White producers received an average MFP payment that was ten times larger than Black farmers (Hayes, 2021). Both ad-hoc government payments were linked to production or planted acres causing larger and more productive farms to receive a larger payment. On average, Black farms tend to be smaller than White farms. In 2017, the average

Black farm size and White farm size was 125 acres and 431 acres, respectively (USDA NASS, 2019).

Racial discrimination in government programs has remained a long-standing issue among Black producers. Prominent historical issues included the broken promise of 40 acre and a mule, the 1933 Agricultural Adjustment Act, and the Pigford versus Glickman lawsuit. In 1865, President Abraham Lincoln created the first systematic attempt of reparations to newly freed slaves by providing a mule and 40 acres of land. This program was quickly overturned by President Johnson later the same year (Gates, 2015). The 1933 Agricultural Adjustment Act was a paid diversion program during the Great Depression. The program limited agricultural production of many staple crops and caused thousands of Black sharecroppers to lose their job, pay higher food prices and move to northern cities for new employment opportunities (Minorities and the New Deal). Pigford versus Glickman was a class action lawsuit filed against the USDA for racial discrimination towards Blacks between 1981 and 1996. Black producers claimed that they were being denied loans at a higher rate or having longer wait times for loan approval than White producers which resulted in higher foreclosure and weaker financial situations (Cowan & Feder, 2012).

Two types of analysis were utilized in this paper to measure the racial gap in 2018 MFP payments and 2017 total government payments. The first analysis examined the differences by race in the 2018 MFP payment eligibility using a two-way and three-way decomposition formula. The decomposition measured how much of the difference in payments for each race was due to differences in yield, acreage and the share of crops produced. The second analysis utilized six regressions that estimated the average difference in total government payments in 2017 for Black only farms compared to White only farms. The decompositions concluded that conditional on a

particular farm size, the 2018 MFP payment formula provided a larger eligibility for Black<sup>1</sup> farms compared to White farms. But because approximately seventy percent of Black farms are in the very low sales family farm category, they were not eligible for as large of an average MFP payment as other farm size categories. In all six regressions, Black only farms had an average 2017 total government payment that was less than a White only farms conditional on agricultural factors.

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<sup>1</sup> In this thesis, a Black farm is a farm where at least one of the four operators reported that they were Black or African American and no other race for the 2017 United States Census of Agriculture. A White farm is a farm where at least one of the four operators reported that they were White and no other race for the 2017 United States Census of Agriculture.

## **Chapter 2 - History of Discrimination in Agriculture**

The United States Department of Agriculture defines a socially disadvantaged farmer and rancher (SDFR) as someone belonging to a group(s) that has been subject to racial or ethnic prejudice. Socially disadvantaged farmers and ranchers are producers who are Black or African American, American Indian or Alaska Native, Hispanic or Latino and Asian or Pacific Islander. Women are included as part of SDFR for certain USDA Programs (USDA ERS 2022). The 2017 Census of Agriculture provided data on the demographic, government payments and average farm size results by race and ethnicity of farm producers (up to four producers per farm) (Table 3). According to the 2017 Census of Agriculture, racial and ethnic minorities make up 7.8 percent of all producers in the United States (USDA ERS, 2022).

The 2017 Agricultural Census found that 1.3 percent of U.S. producers were Black. These 45,508 producers farmed primarily in the southeast and mid-Atlantic, had an average farm size of 125 acres and were male. In comparison, 1,963,286 farms were White and had an average farm size of 431 acres (USDA NASS, 2017). In 2017, Black farms and White farms made up 0.27 percent and 97.18 percent of the share of market value of agricultural products (Giri et al., 2022). Sixty-three percent of Black farms specialized in livestock production with the majority, at forty-nine percent, specialized in beef cattle. In 2017, the U.S. Agricultural Census reported Black producers received \$52 million (0.6%) and White producers received 8.8 billion (99%) of total government payments (USDA NASS, 2017).

After emancipation in 1863, racial discrimination in government programs remained a long-standing issue among Black producers. In 1865, President Abraham Lincoln attempted to create the first systematic attempt of reparations to newly freed slaves by providing a mule and 40 acres of land along the coastline stretching from Charleston, South Carolina to the St. Johns River

in Florida. This promise was broken when President Johnson took office and overturned the order later the same year (Gates, 2015). The 1933 Agricultural Adjustment Act paid subsidies to mainly White landlords to reduce farm production of many staple crops such as cotton, corn, and wheat to increase food prices and benefit producers' economic health during the Great Depression. Limiting agricultural production caused thousands of Black sharecroppers to lose their job, pay higher food prices and even move to northern cities for new employment opportunities (Minorities and the New Deal.).

Since the 1990s, there has been five lawsuits filed by Blacks, Hispanics, American Indian and female producers against the United States Department of Agriculture (USDA) and particularly the Farm Service Agency concerning discrimination in loan programs (USDA NRCS). Pigford versus Glickman was a class action lawsuit filed against the USDA for racial discrimination towards Blacks between 1981 and 1996 based on their allocation of farm loans and debt restructure. Black producers claimed that they were being denied loans at a higher rate or having longer wait times for loan approval than White producers. They argued that loan denial and prolonged wait times resulted in higher foreclosure and weaker financial situations. In 1999, The United States District Court in the District of Columbia authorized a settlement agreement for the Pigford versus Glickman discrimination lawsuit. The settlement consisted of two different options depending on the dollar amount of damages. The faster option (Track A) provided \$50,000, loan forgiveness and offsets of tax liability and the slower option (Track B) provided a larger and unique payment than Track A if the claimant could prove that they accrued larger damages than what was compensated for in Track A (Cowan & Feder, 2012).

In another investigation of this issue, Cook (2007) reviewed U.S. Census of Agriculture data and argued that payment discrepancies could not be fully attributed to the fact that, on average,

Blacks operated smaller farms, with lower yields and tended to grow non-program crops. He believed that discrimination at local USDA offices has limited Black producers from expanding their farms and discouraged them from growing subsidized crops resulting in significant gaps in Black and White producer subsidy payments. Between the three-year period of 2003 to 2005, Black cotton producers received an average of \$12,174 while all other producers received an average of \$38,278 (Cook, 2007).



## Chapter 3 - U.S. - China Trade War and MFP

The Market Facilitation Program (MFP) provided compensation to producers in the form of direct payments to offset the impact of retaliatory tariffs on their traditional export markets. The tariffs were imposed by China, Canada, Mexico, the European Union, Turkey, and India (“Market Facilitation Program (MFP) Fact Sheet,” 2018). These six trading partners imported half of all U.S. agricultural exports prior to the trade war (U.S. Government Accountability Office, 2021). President Donald Trump authorized the USDA to make these payments through the Commodity Credit Corporation (CCC). The USDA agreed to distribute up to \$10 billion in the 2018-19 crop marketing year and \$14.5 billion in the 2019-20 crop marketing year. Non-specialty crops collected 94.5 percent of the MFP payment while specialty crops, dairy and hog producers received 1.5 and 4 percent, respectively (U.S. Government Accountability Office 2021).

Different payment formulas were utilized in the two crop marketing years. The 2018 MFP Payment (MFP1) to a producer for non-specialty and specialty crop  $j$  was:

### Equation 1: MFP1 Payment Formula

$MFP1_j = 2018 \text{ production}_j \times \text{the MFP1 payment rate}_j$ , where

$MFP1_j \text{ payment rate} = \text{estimated trade damage} \div 2017 \text{ production}_j$

For example, a producer who harvested 100,000 bushels of corn received  $100,000 \times 0.01 = \$1,000$  (see Table 1 for payment rates). The MFP Commodity Payment Rate was determined by the expected decline in export value to the tariff imposing countries divided by the total United States production of the commodity (Janzen and Hendricks 2020). Trade damages were estimated as the expected loss in exports compared to the baseline exports. Baseline exports were defined as 2017 exports for MFP1. Due to uncertainty concerning the potential length of the trade war, there

were two payments made during 2018, each weighted by one-half of the MFP rate provided by the USDA (“Market Facilitation Program (MFP) Fact Sheet,” 2018).

**Table 1: Commodities included in both MFP1 and MFP2, their payment rates and changes between the two crop marketing years**

Commodity Payment Rates				
Commodity (Unit)	MFP1 Payment Rate (\$/Unit)	MFP2 Payment Rate (\$/Unit)	Change (%)	
Corn (Bushels)	\$0.01	\$0.14	1300%	
Cotton (Pounds)	\$0.06	\$0.26	333%	
Wheat (Bushels)	\$0.14	\$0.41	193%	
Shelled Almonds (Pounds)	\$0.03	\$0.07	127%	
Sorghum (Bushels)	\$0.86	\$1.69	97%	
Dairy Milk (Hundredweight)	\$0.12	\$0.20	67%	
Soybeans (Bushels)	\$1.65	\$2.05	24%	
Hogs (Number of Head of Live Hogs on Preferred Date)	\$8.00	\$11.00	38%	
Fresh Sweet Cherries (Pounds)	\$0.16	\$0.17	6%	

Source: (“Market Facilitation Program Fact Sheet,” 2019; “Market Facilitation Program (MFP) Fact Sheet,” 2018)

In 2019, MFP2 was announced and included 27 non-specialty crops, 10 specialty crops and 2 livestock animals (Table 2). The payment for non-specialty crops in 2019 (MFP2) was estimated differently than in 2018 and the payment program was not linked to 2019 commodity-specific production because policymakers did not want to disrupt production decisions. For example, policymakers did not want overproduction of soybeans due to the MFP1 Commodity Payment Rate being the highest. Instead, MFP2 was linked to total planted acres (Janzen & Hendricks, 2020). The MFP2 commodity payment rates changed because the baseline export definition for

MFP2 reflected the maximum exports between 2009 and 2018 whereas the MFP1 commodity payment rate used the 2017 exports as the baseline (Table 1). The payments for non-specialty crops were estimated as:

**Equation 2: MFP2 Payment Formula**

$MFP2_j = \text{total planted acres of MFP eligible crops in 2019} \times \text{the single-county payment rate}_j$

where

$\text{Single County Payment Rate}_j = \text{estimated trade damage} \div \text{total fixed historical acres}_j$

where

$\text{Estimated Trade Damage} = \sum (\text{Fixed Historical Acres} \times \text{Fixed Historical Yield} \times \text{MFP2 Crop Commodity Payment Rate}_j)$

and

$\text{Total Fixed Historical Acres} = \sum \text{Historical Acres of All Eligible Commodities.}$

The single-county payment rate ranged between \$15 and \$150 per acre and was determined by the impact of retaliatory tariffs on crops grown in the county, and not necessarily to crops grown by the individual. A producer would receive a high county payment rate if they farmed in a county where other producers were planting crops that were heavily impacted by the trade war. In general, single-county payment rates were highest in the South where cotton, sorghum and soybeans are common cropping mixes and these were crops heavily impacted by the trade war (U.S. Government Accountability Office, 2021). The largest MFP2 payments per farm occurred in Nueces County, Texas and Coahoma County, Mississippi where the single-county payment rates were \$147/acre and \$150/acre, respectively (Janzen & Hendricks, 2020). Specialty crops received a payment based on acres of fruit or nut bearing plants in 2019. Dairy producers received a per hundredweight payment based on production history and hog producers received a payment based

on the number of live hogs owned on a selected day between April 1<sup>st</sup> to May 15<sup>th</sup>, 2019 (“Market Facilitation Program Fact Sheet” 2019).

The baseline export definition change created skewed trade loss data resulting in significant increases in payment rates for corn and cotton which had significantly more exports prior to 2017 (Janzen & Hendricks, 2020). Fourteen of the twenty-nine MFP2 crops had a higher baseline export value than any retaliating country’s import value between 2009 and 2018. This was a result because the USDA included policy factors such as nontariff barriers (U.S. Government Accountability Office, 2021). This resulted from the two different methodologies used. The first method was the summation of values from two different retaliatory countries across two years. For example, the baseline value for corn was estimated by the summation of Chinese imports in 2012 (\$1658 million) and European Union imports in 2018 (\$349 million) to give a total MFP2 corn baseline of \$2 billion. The second method was the summation of the highest values of different harmonized system (HS) codes for a commodity across two years. The HS code is used to identify traded commodities and each species of the commodity has its own unique code. For example, the baseline value for wheat was calculated using the sum of HS codes for durum wheat and other wheat. The USDA summed the Chinese import value of \$289 million in 2018 for durum and \$1.1 billion in 2013 for other wheat to create the wheat baseline of \$1.4 billion (U.S. Government Accountability Office, 2021). All five of the non-specialty crops in MFP1 had a higher baseline export value for MFP2. The corn baseline export value jumped to six times the amount of the MFP1 baseline value (U.S. Government Accountability Office, 2021).

Soybean producers in the Corn Belt states benefitted the most from MFP1 and received seventy-five percent of total payments (Glauber, 2019). In 2019, soybean producers received 33.2 percent of total MFP1 payments. Most soybean producers also produced corn which accounted for

35.7 percent of total payments in 2019. Combining both crop percentages, producers who planted both corn and soybeans received 68.9 percent of total payments (Glauber, 2019). Soybean producers reaped the largest benefits from MFP because they experienced the greatest losses in exports of all agricultural commodities. Prior to the trade war, one-half of all United States soybeans were exported, and one-half of the exported beans went to China. During the 2018-19 crop marketing year, United States soybean exports to China dropped sixty-five percent. United States soybean exports to the rest of the world did not increase enough to compensate for Chinese tariffs during the trade war (Adjemian et al. 2019).

**Table 2: Crops added to MFP2 and their payment rates**

Commodity (Unit) <sup>1</sup>	MFP1 Payment Rate (\$/Unit)
Rice (Hundredweight)	\$0.63
Peanuts (Pounds)	\$0.01
Lentils (Hundredweight)	\$3.99
Peas (Hundredweight)	\$0.85
Alfalfa Hay (Tons)	\$2.81
Dried Beans (Hundredweight)	\$8.22
Chickpeas (Hundredweight)	\$1.48
Tree Nuts (Acre) <sup>2</sup>	\$146.00
Fresh Grapes (Pounds)	\$0.03
Cranberries (Pounds)	\$0.03
Ginseng (Pounds)	\$2.85

<sup>1</sup>The USDA used \$0 as a payment rate for barley, canola, flaxseed, millet, mustard seed, oats, rapeseed, rye, safflower, sesame seed, sunflower seed, and triticale. Barley, crambe, millet, rye and triticale were not impacted by the tariffs. Canola, flaxseed, mustard seed, oats, rapeseed, safflower, sesame seed and sunflower seed were affected by tariffs, but the sum of the trade value

of exports to tariff imposing entities was minimal. Producers of these 13 crops could receive MFP payments at their county rate because these crops could have experienced indirect effects from market changes from the tariffs (U.S. Government Accountability Office 2021).

<sup>2</sup>Tree nuts are almonds, hazelnuts, macadamia nuts, pecans, pistachios, and walnuts.

Source: (U.S. Government Accountability Office, 2021)

In the short run, the Market Facilitation Program provided aid that was larger than the decrease in crop prices due to the trade war (Janzen & Hendricks, 2020). MFP completely offset retaliatory tariffs in many Midwest states' economy such as Iowa, North Dakota, Nebraska, and Kansas (Balisteri, Zhang, and Beghin 2020). Many Midwest states rely on agriculture as a source of income and produce crops that were most effected by retaliatory tariffs. Although producers experienced net welfare gains during the trade war, long term effects could impact the nation's agricultural sector. During the trade war trade diversion occurred, and the United States could now be viewed as an unreliable trade partner (Janzen and Hendricks 2020).

Yu et al. (2022) estimated the effect of changes in tariff levels in 2018 of U.S. field crop on income from cropland rentals. The authors found that a one percent increase in the localized tariff resulted in a three percent decline in land rents if there was no government support.

Adjemian, Smith, and He (2021) found the average relative price of soybeans decreased by 17.6% between June to November 2018. The price decline for soybeans was less than the twenty-five percent tariff which implies that U.S. producers exported to non-retaliatory countries, increased domestic consumption, or stored their commodity. Grant et al. (2021) used a monthly gravity model to estimate that U.S. exports to China decreased by seventy-six percent. Janzen and Hendricks (2020) calculated that there was a sixty-five percent change in exports after the tariff was implemented.

Zheng et al. (2018) used an ex-ante global simulation model and they predicted that pork export value to China would decrease by 83.3 percent and the price of domestic pork would decline 0.6 percent. Nti, Kuberka, and Jones (2019) found the export value of pork declined 23% between mid-2018 to 2019. U.S. pork exports to China fell when the tariff was implemented, but in August 2018 Chinese pork supply fell and prices increased in response to their first outbreak of African Swine Fever. China responded to the outbreak and the demand for imported pork grew even though the tariff was still in effect (Nti et al., 2019).

Contrarily, corn experienced less of a decline in export value and price compared to soybeans because less than one percent was exported to China in 2017. U.S. corn exports have declined since 2007 due to domestic demand for corn-based ethanol (Grant et al., 2021). Corn export value did not decrease significantly, but domestic corn and soybean prices fell 7% and 10% at the height trade tensions between June 15<sup>th</sup> to July 15<sup>th</sup>, 2018 (Swanson et al., 2018).

Trade losses in cotton were estimated to be small than soybeans larger than corn. In 2017, the U.S. exported 17% of its cotton to China (Muhammad et al., 2019). U.S. cotton exports to China have declined since its peak in 2011-12 because the Chinese built up their state cotton reserve and began selling their cotton domestically in 2015-16 (Muhammad et al., 2019). Carter and Steinbach (2020) estimated U.S. cotton trade volumes to decrease by \$7 million and for retaliatory countries to increase their cotton imports from non-retaliatory countries by \$0.127 billion. In January of 2019, imports from Brazil accounted for approximately fifty percent of all Chinese cotton imports (Muhammad et al., 2019). U.S. cotton exports to China have increased since their low in 2015-16, but the trade dispute has reduced the Chinese import quantity from the United States and favored Brazilian and Australian cotton.

The top seven states with the highest annualized losses were in the Midwest. Iowa, Illinois, and Kansas experienced the greatest losses of \$1.46 billion, \$1.41 billion, and \$955 million respectively (Morgan et al., 2022). These three states accounted for 16.8 percent of the share of 2017 U.S. agricultural exports, but endured 28.9 percent of the share of losses from the retaliatory tariffs. Many midwestern states suffered the greatest losses because of their large production of soybeans, sorghum, pork, wheat, and corn (Morgan et al., 2022).

California experienced the eighth highest annualized losses at \$683 million due to their specialty crop and dairy production. Processed and fresh fruits, dairy products and tree nuts accounted for fifty-four, ten and twenty-nine percent of their total losses (Morgan et al., 2022). In 2017, California had the largest share of agricultural exports, but the state only accounted for 5.2 percent of the total U.S. losses from the tariffs. The disproportionate percent of losses is attributed to their small hog, grain and oilseed sectors (Morgan et al., 2022). Carter and Steinbach (2020) estimated fresh fruit trade volumes to increase by \$51 million and processed fruit to decrease by \$0.158 billion. United States trade volumes to non-retaliatory tariffs for fresh fruit and processed fruit were \$47 million and \$17 million respectively. Dairy product trade volumes were estimated to decline by \$0.367 billion and U.S. trade volumes to non-retaliatory countries were projected to increase by 43 million. Overall, trade destruction outweighs trade deflection for fresh/processed fruits and dairy products which indicates that U.S. producers struggled to acclimate to non-retaliatory country markets and surplus supply was stored or sold in the domestic market (Carter & Steinbach, 2020). Prior to the trade war, the United States exported twenty-three percent of their pecan and six percent of their walnut production to China. Pecan and walnut producers saw a twenty-three percent and six percent decline in value of exports to China. Tree nut producers also

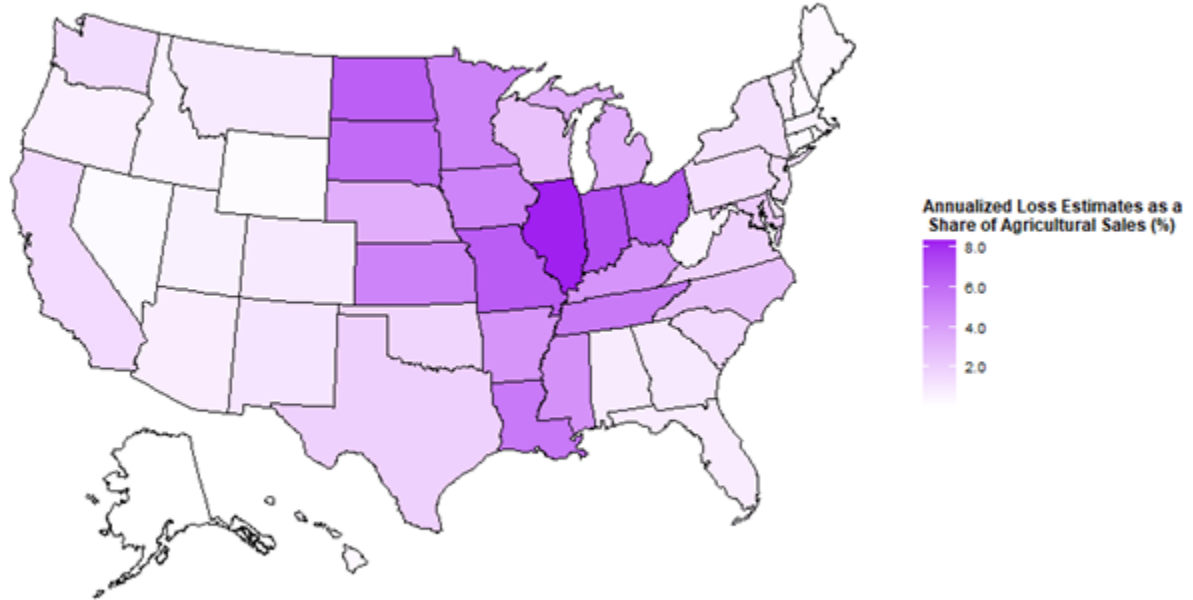


faced unique crop challenges because nuts are reliant on exports, acreage cannot adapt quickly to changes and it is difficult to find new export destinations (Sumner et al., 2019).

Figure 1 estimates the annualized losses in U.S. agricultural export cash receipts due to the retaliatory tariffs as a share of state total agricultural sales. Illinois and Indiana have the largest impact at 8.28 percent and 7.06 percent respectively. This can be attributed to their large soybean production and location along the Ohio and Mississippi River. This indicates that U.S. agricultural exports makes up a significant percentage of the states' total agricultural sales. Other notable states include Arkansas, Tennessee, Mississippi, and Louisiana which all lie along the Mississippi River and are large commodity suppliers to the Gulf of Mexico. Iowa, Illinois, and Kansas were the states with the top annualized losses in U.S. agricultural export cash receipts. Kansas and Iowa ranked 10<sup>th</sup> and 11<sup>th</sup> when estimating losses as a share of agricultural sales because they rely less on the export market than Illinois and Indiana.

**Figure 1: Estimated Annualized Losses in U.S. Agricultural Export Cash Receipts as a Share of State Agricultural Sales**

**Estimated Annualized Losses in U.S. Agricultural Export Cash Receipts as a Share of State Agricultural Sales**



Estimates reflect annualized losses calculated using data from mid-2018 through the end of calendar year 2019 and state agricultural sales data is from 2017.

Source: Morgan, Stephen, Shawn Arita, Jayson Beckman, Saquib Ahsan, Dylan Russell, Philip Jarrell, and Bart Kenner. 2022. “The Economic Impacts of Retaliatory Tariffs on U.S. Agriculture.” and Kansas State University using data from USDA, NASS, Agricultural Sales

## **Chapter 4 - Data and Methodology**

The research utilized the 2017 United States Census of Agriculture's raw micro-data to measure the eligibility of a producer to receive the MFP payments and to estimate total government payments for Black only farms using simple and multi-variable regressions. The Census of Agriculture is administered every five years and measures the total number of farms and ranches in the U.S. including details of up to four operators. The Census of Agriculture defines a farm or ranch as an operation with agricultural sales of at least \$1,000 (USDA NASS, 2017). The micro dataset contains 429 variables and approximately 1.1 million observations.

The Census of Agriculture asked each operator to report their race and allowed the respondent to select all that applied. The data were manipulated to create dummy variables as race indicators for farms. The race indicators included, but were not limited to, White only, Black only, White in combination with other races and Black alone or in combination with other races. The race dummy variables were not mutually exclusive. For example, a farm could be considered a Black only farm and a White only farm when it had at least two operators and if one of the farm's operators indicated they were White and no other races and a different operator on the same farm indicated that they were Black and no other races. This farm would not have been considered White in combination with other races or Black alone or in combination with other races because both operators only selected that they were one race. A farm would be considered White in combination with other races if at least one of the operators indicated that they were White and that they were another race. The race dummy variables were used when creating the two-way decomposition, three-way decomposition, and multiple regressions. To meet the regression independence criterion, the only race variable used in the regression was the Black farm dummy variable. In this thesis, a Black farm is a farm where at least one of the four operators reported

that they were Black or African American and no other race for the 2017 United States Census of Agriculture.

### **Two-Way Decomposition**

The two-way decomposition was designed to compare two types of farms, farm b and farm w based on their yield and crop acreage. Farm b represented the Black farms and utilized the average yield and average acres among Black farms. Farm w represented the White farms and utilized as the average yield and average acres among White farms. The difference between the MFP payment amounts for Farm b and Farm w indicated if there was a disparity based on race of the operators with respect to MFP payments. The two-way and three-way decomposition only considered yield and acreage of corn, soybeans, wheat, cotton, and sorghum. The decompositions were designed similarly to the methodology found in Key (2019).

Consider MFP1 that provided payments based on production in 2018. MFP1 payments per farm are calculated:

#### **Equation 3: Two-Way Decomposition MFP1 Payment Formula Per Farm**

$$MFP1 = \sum_j r_j y_j a_j$$

where each crop  $j$  had a payment rate  $r_j$  (\$/per unit of output, e.g., \$/bushel)  $y_j$  is the yield (e.g., bushels/acre) and  $a_j$  is the number of acres planted to crop  $j$ .

The MFP payments for the White farms and the Black farms were calculated analogously as:

#### **Equation 4: Two-Way Decomposition MFP1 Payment Formula Per White Farm**

$$MFP1_w = \sum_j r_j y_{wj} a_{wj}$$

**Equation 5: Two-Way Decomposition MFP1 Payment Formula Per Black Farm**

$$MFP1_b = \sum_j r_j y_{bj} a_{bj}$$

Note that the payment rate  $r$  is the same for both types of farms, as this is determined by the statute.  $y_{wj}$  was the average yield among White farms (e.g., bushels/acre) and  $a_{wj}$  was the average number of acres planted to crop  $j$  among White farms.  $y_{bj}$  was the average yield among Black farms and  $a_{bj}$  was the average number of acres planted to crop  $j$  among Black farms.

The difference in MFP1 payments received between the White farms and Black farms was calculated as:

**Equation 6: MFP1 Two-Way Decomposition Formula**

$$MFP1_w - MFP1_b = \sum_j r_j (y_{wj} - y_{bj}) \bar{a}_j + \sum_j r_j \bar{y}_j (a_{wj} - a_{bj})$$

where  $\bar{a}_j$  and  $\bar{y}_j$  were the average acreage and yields of both types of farms, respectively.

The difference in MFP payments between the farms was decomposed into two components: the effect due to differences in yields and the effect due to differences in the endowment of land. Note that the decomposition is exact, but the effect of farm size and crop allocation cannot be disentangled.

**Three-way Decomposition**

The three-way decomposition was designed to compare two types of farms, White farms and Black farms based on their yield, total acreage, and crop shares. To distinguish between total acreage and crop shares let:

**Equation 7: Three-Way Decomposition MFP1 Payment Formula Per Farm**

$$MFP1 = a \sum_j r_j y_j s_j$$

where each crop  $j$  had a payment rate  $r_j$  (\$/per unit of output, e.g., \$/bushel),  $a$  was total cropland acres,  $y_j$  was the yield (e.g., bushels/acre) and  $s_j$  was the *share* of total acres planted to crop  $j$  (acres harvested of crop  $j$  divided by  $a$ ).

The MFP1 payments for the White farms and Black farms were calculated analogously as:

**Equation 8: Three-Way Decomposition MFP1 Payment Formula Per White Farm**

$$MFP1_w = a_w \sum_j r_j y_{wj} s_{wj}$$

**Equation 9: Three-Way Decomposition MFP1 Payment Formula Per Black Farm**

$$MFP1_b = a_b \sum_j r_j y_{bj} s_{bj}$$

where each crop  $j$  had a payment rate  $r_j$  (\$/per unit of output, e.g., \$/bushel),  $a_w$  was average cropland acres for White farms,  $y_{wj}$  was the average yield of crop  $j$  for White farms (e.g. bushels/acre) and  $s_{wj}$  was the average *share* of total acres planted to crop  $j$  for White farms (acres harvested of crop  $j$  divided by  $a_w$ ).  $a_b$  was the average cropland acres for Black farms,  $y_{bj}$  was the average yield of crop  $j$  for Black farms and  $s_{bj}$  was the average share of total acres planted to crop  $j$  for Black farms.

The MFP1 payment difference received between White farms and the Black farms is shown as:

**Equation 10: Three-Way Decomposition MFP1 Formula**

$$MFP1_w - MFP1_b \cong \bar{a} \sum_j r_j (y_{wj} - y_{bj}) \bar{s}_j + \bar{a} \sum_j r_j \bar{y}_j (s_{wj} - s_{bj}) + (a_w - a_b) \sum_j r_j \bar{y}_j \bar{s}_j$$

where  $\bar{a}$ ,  $\bar{s}_j$  and  $\bar{y}_j$  were the average total acreage, shares, and yields (average of both types of farms), respectively.

The difference in MFP1 payments between the farms were decomposed into three components based on differences in yields, allocation of land, and total acreage.

## Regressions

The descriptive regression analysis consisted of six level-level simple and multi-variable regressions that estimated the average difference in total government payments in 2017 for Black farms compared to White farms. The regressions did not imply any causal effects of total government payments when a farm is Black, but it showed on average, how much more or less money Black farms received when holding some agricultural factors constant. All regressions were weighted with the weight provided by USDA-NASS and used heteroskedastic robust standard errors.

The simple regression included a dummy variable for a Black farm as the independent variable and total government payments as the dependent variable,

### Equation 11: Regression 1

$$GovPayments_i = \beta_0 + \beta_1 BlackFarm_i + \varepsilon_i$$

where  $GovPayments_i$  represented the amount of government payments in 2017.  $\beta_0$  was the regression intercept,  $\beta_1$  was the regression coefficient for the dummy variable that indicated if a farm was Black ( $BlackFarm_i$ ) and  $\varepsilon_i$  was the error term. A farm was Black if at least one of the four operators reported that they were only Black or African American for the 2017 Census of Agriculture. The coefficient  $\beta_1$  indicated the difference in total government payments in dollars that Black farms received compared to White only farms in 2017. The subscript  $i$  represented an individual farm.

The five multi-variable regressions estimated the average difference in total government payments in 2017 for Black farms compared to White farms and used a combination of independent variables including dummy variables for a Black farm, farm size, region of the United States, the farm type, if the first operator was female and county fixed effects. Table 13 in Appendix A shows the region dummy variable categories in the United States. Table 14 in Appendix A shows the farm types represented in the Census of Agriculture and each individual

farm is assigned one of the sixteen farm types. Finally, the dummy variable for if the first operator was female indicated the sex of the first operator. The female operator one dummy variable was included in the regressions because females are occasionally included in USDA socially disadvantaged farmer or rancher programs. As additional variables were added, the regressions' coefficients changed based on their effect on a farm's total government payments. One group was removed to avoid violating the rule of independence in each of the dummy variables. The Corn Belt was removed in the region variable, and grains, oilseeds, dry beans, and dry peas was removed in the farm type variable. As a result, the dummy variables' coefficients will be compared to the missing category. For example, the regression coefficient for the South will be compared to the total government payments that the Corn Belt received in 2017. The first multi-variable regression added one additional independent variable,

**Equation 12: Regression 2**

$$GovPayments_i = \beta_0 + \beta_1 BlackFarm_i + \beta_2 GCFI_i + \varepsilon_i$$

where  $GCFI_i$  was the gross cash farm income in thousands of dollars for the individual farm,  $i$ .  $\beta_2$  was the regression coefficient for  $GCFI_i$  and indicated the change in total government payments in 2017 for a one thousand dollar increase in gross cash farm income for the individual farm  $i$ .

Regression 3 was constructed to control for regional and gender's differences in total government payments,

**Equation 13: Regression 3**

$$GovPayments_i = \beta_0 + \beta_1 BlackFarm_i + \beta_2 GCFI_i + \beta_3 Region_i + \beta_4 Female_i + \varepsilon_i$$

where  $Region_i$  was the region in the United States dummy variable or the individual farm  $i$  and  $Female_i$  was the dummy variable that indicated if the first operator was female.  $\beta_3$  was the regression coefficient for  $Region_i$  and indicated if the region of the United States influenced the average total government payments in 2017.  $\beta_4$  was the regression coefficient for  $Female_i$  and



indicated if farms with a female first operator received different average total government payments in 2017 compared to a male first operator. The Corn Belt region dummy variable were removed to avoid violating the rule of independence.

Regression 4 was constructed to control for difference in total government payments among different commodities,

**Equation 14: Regression 4**

$$GovPayments_i = \beta_0 + \beta_1 BlackFarm_i + \beta_3 Region_i + \beta_4 Female_i + \beta_5 Type_i + \varepsilon_i$$

where  $Type_i$  was the farm type dummy variable for the individual farm  $i$ .  $\beta_5$  was the regression coefficient for  $Type_i$  and indicated if producing certain crops or livestock increased the average total government payments a farm received in 2017. The grains, oilseeds, dry beans, and dry peas farm type dummy variable and Corn Belt region dummy variable were removed to avoid violating the rule of independence.

Regression 5 differed from Regression 4 because gross cash farm income was reintroduced into the model to see if it was still important when other independent variables were included,

**Equation 15: Regression 5**

$$GovPayments_i = \beta_0 + \beta_1 BlackFarm_i + \beta_2 GCFI_i + \beta_3 Region_i + \beta_4 Female_i + \beta_5 Type_i + \varepsilon_i$$

Finally, regression 6 included county fixed effects,

**Equation 16: Regression 6**

$$GovPayments_i = \beta_0 + \beta_1 BlackFarm_i + \beta_2 GCFI_i + \beta_4 Female_i + \beta_5 Type_i + \gamma_i + \varepsilon_i$$

where  $\gamma_i$  was a separate intercept (i.e., fixed effect) for the county that the individual farm  $i$  was located in. The county fixed effects indicated if the county that the farm was in influenced the average total government payments in 2017.  $\gamma_i$  was added to the regression as a fixed effect to

measure the difference in average total government payments for Black farms compared to White farms when the farm had the same gross cash farm income, a female first operator, grew the same crop or livestock and farmed in the same county.

## **Chapter 5 - Results**

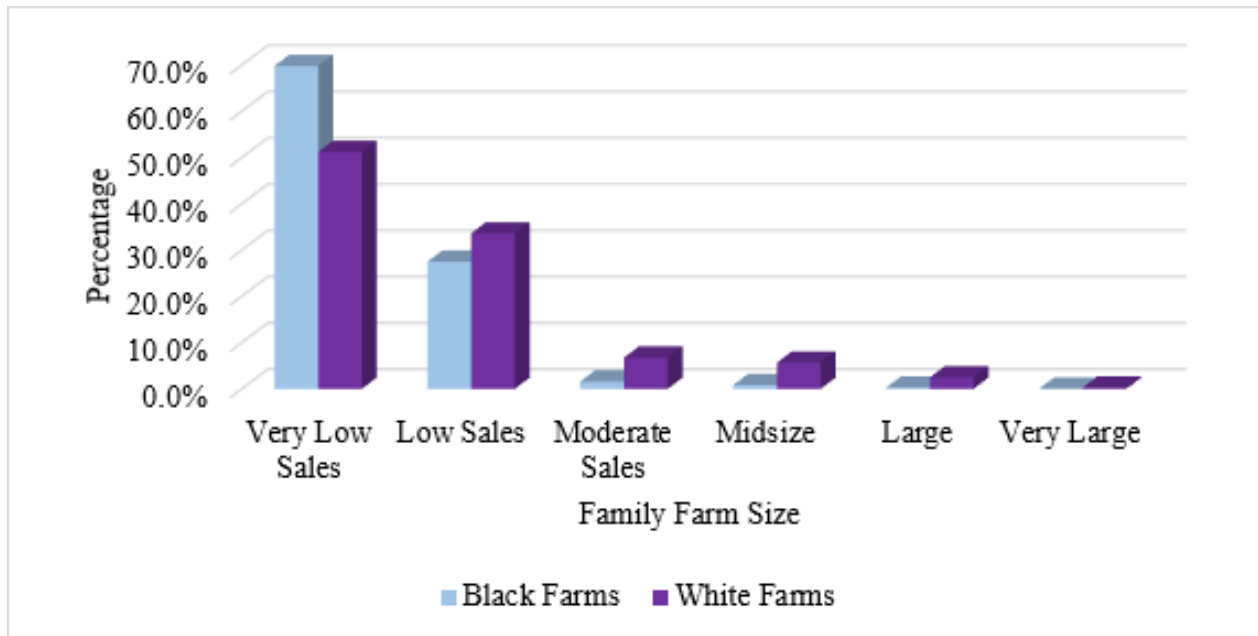
### **2018 MFP Payments by Race**

The first analysis examined the amount of payment from the 2018 Market Facilitation Program (MFP) that farms were eligible to receive and provided a decomposition to measure how much of the difference was due to differences in yield, acreage, and the share of crops produced. The decomposition focused on White farms and Black farms on a national level and three-state specific level using Texas, Alabama, and Mississippi.

### **Summary Statistics**

Black farms tend to be smaller in number and acreage than White farms. For example, 1.6 percent of U.S. farms have at least one operator who is only Black or African American compared to 96.1 percent of farms that have at least one operator who is only White. Approximately seventy percent of Black only farms and fifty-one percent of White only farms are in the very low sales family farm category while only 0.3 percent of Black only farms and two percent of White only farms are in the large family farm size category (Figure 2). Similar figures were found when comparing Black alone or in combination with other races and White alone or in combination with other races' very low sales family farms counts. According to the 2017 Census of Agriculture, the average Black only and White only farm was approximately 125 acres and 431 acres, respectively. Similar values were found for Black alone or in combination with other races and White alone or in combination with other races with average acreage of 132 and 431 acres, respectively (USDA NASS, 2019).

**Figure 2: Percentage of Each Family Farm Size Category by Race**



White farms were eligible to receive substantially more in 2018 MFP payments than Black farms especially when the midsize and large family farm sizes were considered. The weighted average 2018 MFP eligible payment when all crops were included (i.e., corn, soybeans, sorghum, cotton, wheat, sweet cherries, almonds, dairy and hogs) for White only farms and Black only farms was \$4,814 and \$1,032, respectively (Table 3). When only considering farms that were eligible for a positive 2018 MFP payment, White farms were eligible to receive payments that was more than four times larger than Black farms on average. The discrepancy indicates that many Black farms did not grow 2018 MFP eligible crops because when only Black producers who grew the crops were considered, the average eligible payment increased compared to when all Black only producers were included. This conclusion is in line with previous evidence that showed forty-nine percent of Black farms specialized in beef cattle production which was not an MFP eligible commodity (USDA NASS, 2019).

The sum of the 2018 MFP payment using the 2017 Census of Agriculture dataset, overestimated the total payment amount for all producers by \$918 million (USDA, NASS 2019).

In 2018, the USDA agreed to distribute up to \$10 billion in response to the trade war with China, but the actual payout amounted to \$8.6 billion, but the calculation using the 2017 Census of Agriculture dataset indicates \$9.5 billion of total payments (U.S. Government Accountability Office 2021).

Black only farms were estimated to receive \$33.95 million in 2018 MFP payments when the 2017 Census of Agriculture data was utilized. An analysis of actual MFP payments by Giri et al., found that Black only farms received \$40.35 million, or 0.17 percent of the total share of 2018 and 2019 MFP payments. My estimate of 2018 MFP payments for Black farms is different than the findings from Giri et al. However, Giri et al., estimates the payments at the beneficiary level and I estimate it at the farm level. My estimate attributed a payment to a Black farm when the farm had at least one Black operator while Giri et al., attributed half of the payment to a Black operator and half of the payment to a White operator if there was both a Black and White operator on the farm.

Table 6 and 7 show the estimated payments by commodity using aggregate USDA-NASS production data in 2017 and 2018 compared to the actual 2018 MFP payments by commodity. The largest percentage differences in the MFP payment estimation compared to the actual MFP payment was in almonds, cherries, and hogs.

**Table 3: Average MFP and Sum of 2018 MFP eligibility for all farms, White farms, and Black farms using all crops for all farms (i.e., corn, soybeans, wheat, cotton, sorghum, sweet cherries, almonds, hogs, and dairy)**

	Mean MFP (All MFP eligible crops)	Mean MFP if greater than zero dollars (All MFP eligible crops)	Sum
All Producers	\$4,661	\$18,651	\$9,518,478,167
White Only	\$4,814	\$18,810	\$9,451,630,496
Black Only	\$1,032	\$7,762	\$33,951,350

White Alone or In Combination with Other Races	\$4,797	\$18,787	\$9,463,858,242
Black Alone or in Combination with Other Races	\$1,141	\$8,337	\$40,461,739

Table 4 shows the average MFP payment by race category and farm size across all farms and all 2018 MFP commodities. Table 5 shows the same information, but it gives the average payment only among those farms that were eligible to receive a positive payment. Among family farms with very low sales or low sales, White farms were eligible to receive larger payments than Black farms (Tables 4 and 5). For example, among low sales producers who were eligible for a payment, White only farms were eligible for a payment of \$3,802 while Black only farms were eligible for a payment of \$3,438 (Table 5). When considering moderate sales, midsize and large family farms who were eligible to receive a payment, Black farms had a larger average payment than White farms. This shows that conditional of a particular farm size, the payment formula was larger for Black farms, but because approximately seventy percent of Black farms are in the very low sales family farm category, they were not eligible for as large of an average MFP payment.

**Table 4: Weighted average 2018 MFP eligibility by race and size category using all commodities for all farms**

	White Only	Black Only	White Alone or in Combination with Other Races	Black Alone or in Combination with Other Races
Very Low Sales Family Farms	\$21	\$19	\$21	\$19
Low Sales Family Farms	\$1,143	\$742	\$1,140	\$740

Moderate Sales Family Farms	\$8,989	\$10,932	\$8,978	\$9,893
Midsized Family Farms	\$26,313	\$33,156	\$26,303	\$32,977
Large Family Farms	\$67,298	\$88,885	\$67,267	\$82,191

**Table 5: Weighted average 2018 MFP eligibility by race and size category using all commodities for farms with an MFP greater than zero dollars**

	White Only	Black Only	White in Combination with Other Races	Black alone or in combination with other races
Very Low Sales Family Farms	\$286	\$246	\$286	\$238
Low Sales Family Farms	\$3,802	\$3,438	\$3,798	\$3,371
Moderate Sales Family Farms	\$13,522	\$19,530	\$13,519	\$18,284
Midsized Family Farms	\$32,848	\$45,991	\$32,847	\$45,636
Large Family Farms	\$80,920	\$109,871	\$80,914	\$107,281

**Table 6: Estimated 2018 MFP Payment versus Actual 2018 MFP Payment Using 2017 Production**

Commodity	Payment Rate	Unit	2017 Production	Estimated MFP Payments Based on 2017 Production	Actual 2018 MFP Payments	2017 % Difference
Almonds	0.03	Per lb.	2,270,000,000	\$ 68,100,000	\$ 21,920,832	211%
Cherries	0.16	Per lb.	875,100,000	\$ 140,016,000	\$ 42,686,136	228%
Corn	0.01	Per bu.	14,609,407,000	\$ 146,094,070	\$ 133,516,416	9%
Cotton	0.06	Per lb.	10,042,800,000	\$ 602,568,000	\$ 484,079,607	24%
Dairy	0.12	Per cwt.	2,155,270,000	\$ 258,632,400	\$ 182,351,567	42%
Hogs	8	Per head	67,192,000	\$ 537,536,000	\$ 155,584,790	245%
Sorghum	0.86	Per bu.	361,871,000	\$ 311,209,060	\$ 244,554,948	27%
Soybeans	1.65	Per bu.	4,411,633,000	\$ 7,279,194,450	\$ 7,069,337,583	3%
Wheat	0.14	Per bu.	1,740,910,000	\$ 243,727,400	\$ 241,620,706	1%
<b>Total</b>				\$ 9,587,077,380	\$ 8,575,652,585	12%

**Table 7: Estimated 2018 MFP Payment versus Actual 2018 MFP Payment Using 2018 Production**

Commodity	Payment Rate	Unit	2018 Production	Estimated MFP Payments Based on 2018 Production	Actual 2018 MFP Payments	2018 % Difference
Almonds	0.03	Per lb.	2,280,000,000	\$ 68,400,000	\$ 21,920,832	212%
Cherries	0.16	Per lb.	688,800,000	\$ 110,208,000	\$ 42,686,136	158%
Corn	0.01	Per bu.	14,340,369,000	\$ 143,403,690	\$ 133,516,416	7%
Cotton	0.06	Per lb.	8,816,160,000	\$ 528,969,600	\$ 484,079,607	9%
Dairy	0.12	Per cwt.	2,175,680,000	\$ 261,081,600	\$ 182,351,567	43%
Hogs	8	Per head	68,225,900	\$ 545,807,200	\$ 155,584,790	251%
Sorghum	0.86	Per bu.	364,986,000	\$ 313,887,960	\$ 244,554,948	28%
Soybeans	1.65	Per bu.	4,428,150,000	\$ 7,306,447,500	\$ 7,069,337,583	3%
Wheat	0.14	Per bu.	1,885,156,000	\$ 263,921,840	\$ 241,620,706	9%
<b>Total</b>				\$ 9,542,127,390	\$ 8,575,652,585	11%



## National Two-Way and Three-Way Decomposition

Similar weighted MFP eligibility averages for White only farms and Black only farms were found when compared to the representative White and Black farms' averages using the decomposition's crops (Table 8). The decomposition's crops include corn, soybeans, cotton, wheat, and sorghum. Note that \$8.5 billion of payments were made to the crops used in the decomposition compared to a total of \$9.5 billion across all commodities, so the decomposition accounts for roughly eighty-nine percent of MFP payments even though it uses only a subset of the commodities. This table's averages differ from the decomposition because it used the weighted mean of every individual farm's MFP payment eligibility compared to creating an average payment for a representative farm using the average yield and average acres as in the decomposition.

**Table 8: Average MFP and Sum of MFP for all farms, White only farms and Black only farms using only decomposition crops for all farms (i.e., corn, soybeans, wheat, cotton, and sorghum)**

	Mean MFP1 (Only Decomposition Crops)	Sum of MFP1 (Only Decomposition Crops)
All Producers	\$4,152	\$8,478,531,330
White Only	\$4,293	\$8,427,806,681
Black Only	\$978	\$32,191,053

Table 9 shows the results from the two-way and three-way decomposition. The difference in the 2018 MFP payment eligibility between the representative White farm and representative Black farms was \$3,385 for the two-way and three-way national decomposition. The average 2018 MFP payment for a representative White farm and a representative Black farm was \$4,216 and \$831, respectively. The average MFP eligibility among farms (Table 8) is different than the average MFP eligibility of a representative farm (Table 9). For example, the average MFP

eligibility among farms that are White only farms and Black only farms is \$77 and \$147 larger than the average MFP eligibility of a representative White farm and a representative Black farm, respectively.

**Table 9: National Two-Way and Three-Way Decomposition Results**

	<i>Value</i>	<i>Percentage of the Difference</i>
Eligible MFP Payment for Representative White Farm $MFP1_w = \sum_j r_j y_{wj} a_{wj}$	\$4216	--
Eligible MFP Payment for Representative Black Farm $MFP1_b = \sum_j r_j y_{bj} a_{bj}$	\$831	--
<b>Two-way decomposition calculations</b>		
Difference in eligible MFP due to difference in yields $\sum_j r_j (y_{wj} - y_{bj}) \bar{a}_j$	\$651	19%
Difference in eligible MFP due to difference in acreage $\sum_j r_j \bar{y}_j (a_{wj} - a_{bj})$	\$2734	81%
<b>Three-way decomposition calculations</b>		
Difference in eligible MFP due to difference in yields $\bar{a} \sum_j r_j (y_{wj} - y_{bj}) \bar{s}_j$	\$679	20%
Difference in eligible MFP due to difference in crop shares $\bar{a} \sum_j r_j \bar{y}_j (s_{wj} - s_{bj})$	-\$341	-10%
Difference in eligible MFP due to difference in total cropland acres $(a_{wj} - a_{bj}) \sum_j r_j \bar{y}_j \bar{s}_j$	\$3075	90%

When the two-way decomposition was used the difference in the 2018 MFP payment eligibility between the representative farms was composed of effects due to differences in yields and the effect due to differences in acreage. Larger cropland acreage for the representative White

farm attributed to \$2,734, or eighty-one percent, of the difference in eligibility and differences in yield attributed to \$651, or nineteen percent, of the difference.

When the three-way decomposition was used, the difference in the 2018 MFP payment eligibility between the farms was decomposed into effects due to differences in yields, differences in crop shares and the total cropland acres. Larger cropland acreage for the representative White farm contributed to \$3,075 of the difference in eligibility and differences in yield contributed to \$679 of the difference. The representative Black farm produced more MFP eligible crops in their total cropland acres than the representative White farm which contributed to -\$341 of the difference in eligibility. The results from the decompositions confirm that on average, the main influence on why Black farms were eligible for a smaller MFP payment than White farms was because Black farms are smaller rather than Black farms having lower yields or growing crops that are not eligible for MFP. However, some of the difference in MFP payments is attributed to Black farms having lower yields on average.

Belasco and Smith (2022) utilized actual MFP payments from the USDA Farm Service Agency recipient data and found similar results that indicated that larger farms received higher per acre payments for MFP and federal crop insurance. To note, Belasco and Smith (2022) focused on farm size and not racial differences in farm operators. Of all farms that received a payment, the largest ten percent of farms received 52.7 percent of the 2018 MFP payment and 49.2 percent of the 2019 MFP payment (Belasco & Smith, 2022).

### **Texas, Alabama and Mississippi Two-Way and Three-Way Decomposition**

Texas, Alabama, and Mississippi represented approximately 49% of Black only farms in the United States in 2017 and were selected to conduct the two-way and three-way decomposition within a more homogenous region rather than the United States as a whole (USDA NASS, 2017).

For example, it could be that the difference in farm size of yield among Black farms simply represents regional differences in farm size or yield since Black farms tend to be in the South.

Table 10 shows the decomposition results for the three-state region. The difference in the 2018 MFP payment eligibility between the representative White farm and representative Black farm was \$1,406. The 2018 MFP payment for a representative White farm and a representative Black farm in these three states was \$2,008 and \$602, respectively. The payment eligibility was smaller for both representative farm types in these three states compared to the national eligible payment.

**Table 10: Texas, Mississippi, and Alabama Two-Way and Three-Way Decomposition Results**

	<i>Value</i>	<i>Percentage of the Difference</i>
Eligible MFP Payment for Representative White Farm $MFP1_w = \sum_j r_j y_{wj} a_{wj}$	\$2008	--
Eligible MFP Payment for Representative Black Farm $MFP1_b = \sum_j r_j y_{bj} a_{bj}$	\$602	--
<b>Two-way decomposition calculations</b>		
Difference in eligible MFP due to difference in yields $\sum_j r_j (y_{wj} - y_{bj}) \bar{a}_j$	\$33	2%
Difference in eligible MFP due to difference in acreage $\sum_j r_j \bar{y}_j (a_{wj} - a_{bj})$	\$1374	98%
<b>Three-way decomposition calculations</b>		
Difference in eligible MFP due to difference in yields $\bar{a} \sum_j r_j (y_{wj} - y_{bj}) \bar{s}_j$	\$93	6%
Difference in eligible MFP due to difference in crop shares $\bar{a} \sum_j r_j \bar{y}_j (s_{wj} - s_{bj})$	\$152	10%

Difference in eligible MFP due to difference in total cropland acres $(a_{wj} - a_{bj}) \sum_j r_j \bar{y}_j \bar{s}_j$	\$1222	83%
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When the two-way decomposition was used the difference in the 2018 MFP payment eligibility between the farms was composed of effects due to differences in yields and the effect due to differences in crop acreage. Larger acreage for the representative White farm contributed to \$1,374 of the difference in eligibility while differences in yield contributed only \$33 of the difference. The three-state analysis shows a larger acreage effect which was expected, but the yield difference was still present even though the states were in the same region with similar crop portfolios. The findings show that the size of the farm made a larger difference on MFP eligibility in these three states than it did on the national level and the representative Black farm received smaller payments due to their farms being disproportionately smaller than the representative White farm.

When the three-way decomposition was used, the difference in the 2018 MFP payment eligibility between the farms was decomposed into effects due to differences in yields, differences in crop shares and farm size. Larger cropland acreage for the representative White farm contributed to \$1,222 of the difference in eligibility, differences in yield contributed to \$93 of the difference and differences in crop shares contributed to \$152 of the difference. Unlike the national three-way decomposition, the representative Black farm in Texas, Alabama and Mississippi did not produce more MFP eligible crops in their total cropland acres than the representative White farm. Like the national decomposition, the three-state decomposition results confirm that on average, the main factor influencing MFP eligibility for Black farms is farm size compared to yield and crop share.

**Government Payments in 2017 by Race**

The second analysis utilized six descriptive regressions that estimated the average difference in total government payments in 2017 for Black farms compared to White farms. The regressions showed, on average, how much more or less money Black farms received when some agricultural factors were held constant.

**Summary Statistics**

Black farms received smaller total government payments in 2017 on average than White farms (Table 11). On average, White farms received almost double the amount of government payments compared to Black farms. This section explored differences in actual government payments to examine the racial differences in the actual payments received. However, total government payments could not be decomposed as easily as the MFP eligibility because there is no specific formula for the payments. Control variables were added to the regressions to effectively decompose the gap in total government payments between White and Black farms.

**Table 11: Average Total Government Payments by Race**

Race	Mean Total Government Payments	Median Total Government Payments
Black Only	\$6,615.87	\$2,013.60
White Only	\$14,009.02	\$4,276.00
Black Alone or in Combination with Other Races	\$7,108.31	\$2,094.25
White Alone or in Combination with Other Races	\$14,004.04	\$4,271

Multiple regressions were performed with different combinations of variables to explain why Black only farms received less total government payments in 2017 than White only farms (Table 12 and Table 15 in Appendix B). The dependent variable in all the regressions were 2017

total government payments and the key independent variable of interest was “Black farm” which is defined as a farm with at least one operator who indicated that they were Black of African American and no other race. All six of the regressions had statistically significant p-values for the F-Tests. The regressions did not overfit the model because the dataset contained approximately 1.1 million observations.

**Table 12: Total Government Payments Bi-Variate and Multi-Variable Regressions**

Variables	Regression Coefficients					
	(1)	(2)	(3)	(4)	(5)	(6)
Black Farm	-7,394.934*** (307.889)	-5,901.706*** (323.808)	-9,086.101*** (358.510)	-9,824.578*** (357.770)	-8,787.075*** (354.913)	-4,958.789*** (330.101)
Gross Cash Farm Income		5.914*** (0.551)	5.703*** (0.538)		5.533*** (0.543)	5.772*** (0.557)
Female 1 <sup>st</sup> Operator			-4,523.251*** (164.966)	-3,568.697*** (117.226)	-2,817.525*** (130.914)	-2,480.319*** (129.604)
Region Indicator	No	No	No	Yes	Yes	Yes
Farm Type	No	No	No	Yes	Yes	Yes
County Fixed Effect	No	No	No	No	No	Yes
Number of Observations	1161398	1161398	1161398	1161398	1161398	1161398

Note: Heteroskedastic robust standard errors are reported in parentheses under the coefficient. A Black farm is defined as a farm with at least one operator who is Black or Black and no other race. A White farm is a farm with at least one operator who is White and no other race. The sample used in the regression only includes farms that were either defined as a Black farm or a White farm.

\*\*\*Significant at the 1 percent level.

\*\*Significant at the 5 percent level.

\*Significant at the 10 percent level.



The simple bi-variate regression, in column (1), indicated that in 2017, Black farms received an average of \$7394.93 less than White farms in total government payments. The average 2017 total government payments for White farms on a per farm basis was \$14,009.02 and the regression results indicate that Black farms received an average of \$6,614.09 per farm (USDA NASS, 2017). This result concludes that Black farms obtained a payment that was fifty-two percent smaller than White farms. To examine the finding in greater detail, additional variables were included in subsequent regression models to help explain why Black farms received less payments on average than White farms. Considerations included farm size, gender of the primary operator, region, farm type and county fixed effects.

Gross cash farm income was included as a control in column (2) to examine the hypothesis that on average, Black farms received less government payments than White farms because Black farms tend to be smaller in acreage. Gross cash farm income served as a proxy variable for farm size. The regression coefficient indicates that conditional on the farms being the same size, Black farms received an average of \$5,901.71 dollars less in total government payments than White farms. The overall race gap is \$7,394.934 and difference in farm size by race explains \$1,493.23, or twenty percent, of the difference in total government payments.

Another hypothesis is that Black farms are in regions where government payments are smaller or maybe less likely to have female operators. The regression in column (3) utilized dummy variables for a Black farm, farm size, the gender of the first operator and region. Region and gender were utilized to control for disparities in production and because females are occasionally considered in the USDA's socially disadvantaged programs. When the female operator and region variables were included, the average difference in total government payments for Black farms decreased compared to the results in regressions (1) and (2). Conditional on farm

size, region and sex, Black farms received an average of \$9,086.10 less than White only farms. When region and gender of the first operator were included, the coefficient for Black farm decreased substantially. The racial gap became larger when region and gender were included because Black farms are in regions that receive more total government payments. Almost half the Black farms are in the Southeast and Southern Plains region which both received significantly higher government payments than the omitted Corn Belt region.

An additional consideration was that the gap in payments is explained by the fact that Black farms produced different commodities on average. Forty-nine percent of Black only farms specialized in beef cattle production which is not a commodity that is heavily subsidized by the government compared to some crops. The regression in column (4) utilized dummy variables for a Black farm, the gender of the first operator, region, and additionally, farm type. Conditional on farms being in the same region, with a female first operator and farm type, Black farms received an average of \$9,824.58 less than White farms in total government payments. This would argue against the hypothesis that Black farms received less government payments because they produced commodities that were not favorable towards government payments. Of all six regressions, the difference in average total government payments was largest when conditional on gender, region and farm type. Regression (4) indicated that Black farms received a payment that was seventy percent smaller than the average White farm. There is ninety-five percent confidence that Black farms received between \$9,123.35 and \$10,525.81 less than White farms in 2017 total government payments.

Based on regression (4)'s results, it could be argued that although Black farms grew the same commodities and are in the same region, White farms on average are larger than Black farms and this would account for why Black farms received lower total government payments. The

regression in column (5) utilized dummy variables for a Black farm, the gender of the first operator, region, farm type and included gross cash farm income. Conditional on farms being the same gross cash farm income, region, having a female first operator and farm type, Black farms received an average of \$8,787.08 less than White farms. The racial gap became larger when farm type was included because Black farms grew crops that received larger total government payments. The hypothesis that White farms that grew the same crops and were in the same region as Black farms are simply bigger and therefore receive larger government payments is not supported by column (5).

Based on regression (5), it could be argued that the region control is not disaggregated enough to account for differences in land productivity and agricultural practices. The regression in column (6) estimated total government payments in 2017 using dummy variables for a Black farm, gross cash farm income, the gender of the first operator, farm type and county fixed effects. The county fixed effect variable was added to control for differences in payments between counties. Conditional on farms having the same gross cash farm income, gender of the first operator, farm type, and located in the same county, Black farms received an average of \$4,958.79 less than White farms. The Black farm coefficient indicated that the difference in government payments of \$4,958.79 was explained by other reasons than the independent variables that were included in the six regressions. Forty percent of the racial gap in total government payments is explained by farm size, farm type, gender, and the county where the Black farm is located. There is ninety-five percent confidence that Black farms received between \$4,311.79 and \$5,605.79 less than White farms in 2017 total government payments when the independent variables were held constant.

The sixth column gives some evidence that could raise concerns about if Black farms are receiving fair access to government programs, but another explanation to the discrepancy in payments could be due to difference in yield for White and Black farms. Yield could be added to a future regression because many government programs are based on production. A lower yield causes lower production and thus lower payments for Black farms. Yield was not considered in these regressions because it was difficult to compare yields across farms due to farms growing several different crops. There remains an open question as to whether Black farms also received smaller government payments because they were not able to access equal payments due to discrimination at the USDA-Farm Service Agency offices or they lacked information about the programs.

It is also worth noting the magnitude of other coefficients in the regression as these coefficients are interesting in and of themselves. First, farms with women who were the first operator received \$3,347.45 less in total government payments in 2017 than when a male was the first operator. Second, total government payments increased by an average of \$5.73 for every \$1,000 increase in gross cash farm income.

## Conclusion

The Market Facilitation Program (MFP) provided direct payments to U.S. producers to offset the impact of retaliatory tariffs on their traditional export markets. The tariffs were imposed by China, Canada, Mexico, the European Union, Turkey, and India (“Market Facilitation Program (MFP) Fact Sheet,” 2018). Prior to the trade war, these six trading partners imported half of all U.S. agricultural exports (U.S. Government Accountability Office, 2021). The USDA agreed to distribute up to \$10 billion in the 2018-19 crop marketing year and \$14.5 billion in the 2019-20 crop marketing year. Black or Black only producers received only 0.17% of the total share of MFP, but they represented 1.34 percent of producers (Giri et al., 2022).

This research utilized the 2017 United States Census of Agriculture’s raw data to measure the eligibility of a producer to receive the MFP payments and to estimate total government payments for Black only farms compared to White only farms. A two-way and three-way decomposition analysis was conducted to measure the differences in eligibility of 2018 MFP payments. The difference between the MFP payment amounts for a Black farm and a White farm indicated if there was a disparity based on race of the operators with respect to MFP payments. The two-way and three-way decomposition only considered yield and acreage of corn, soybeans, wheat, cotton, and sorghum and excluded sweet cherries, almonds, hogs, and dairy. The difference in MFP payments between the farms was decomposed two ways into effect due to differences in yields and the effect due to differences in crop acreage. The three-way decomposition also included differences in crop shares. The descriptive regression analysis consisted of six regressions that estimated the average difference in total government payments in 2017 for Black farms compared to White farms. The regressions showed on average, how much more or less money Black farms received when holding some agricultural factors constant such as, farm size, region, and county.

The results from the two-way and three-way decompositions on the national and three-state specific level confirm that Black farms were eligible for a smaller payment than White farms. The main factor on why Black farms were eligible for a smaller MFP payment than White farms was farm size compared to yield and crop share. A surprising finding was on the national level, Black farms planted more MFP eligible crops than White farms.

In all six regressions White farms received higher total government payments than Black farms. The difference in payments ranged between approximately \$5,900 and \$8,900. The results give some evidence that could raise concerns about if Black farms are receiving fair access to government programs, but another explanation to the discrepancy in payments could be due to difference in yield for White and Black farms or other factors not included in the regressions.

In conclusion, the MFP payment formula favored Black farms over White farms primarily because White farms are larger than Black farms. Most payment programs are based on a per acre basis and will benefit White farms over Black farms due to their average acreage. These findings do not conclude that payments should not be based on acreage, but it shows that if they are then Black farms will receive lower payments compared to White farms.

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## Appendix A - Regression Regions and Farm Types

**Table 13: Regression Regions**

Region	States Included
Pacific	Hawaii, Alaska, Washington, Oregon, and California
Mountain	Montana, Idaho, Wyoming, Nevada, Utah, Colorado, Arizona, and New Mexico
Northern Plains	North Dakota, South Dakota, Nebraska, and Kansas
Southern Plains	Oklahoma and Texas
Lake	Minnesota, Wisconsin, and Michigan
Corn Belt	Iowa, Missouri, Illinois, Indiana, and Ohio
Delta	Arkansas, Mississippi, and Louisiana
Northeast	Maine, Vermont, New Hampshire, Massachusetts, New York, Connecticut, Rhode Island, Pennsylvania, New Jersey, Delaware, and Maryland
Appalachia	Kentucky, West Virginia, Virginia, Tennessee, and North Carolina
Southeast	South Carolina, Georgia, Alabama, and Florida

**Table 14: Farm Classification Codes**

Farm Classification Code	Farm Type
1	Grains, Oilseeds, Dry Beans, Dry Peas
2	Tobacco
3	Cotton
4	Vegetables, Melons, Potatoes, and Sweet Potatoes
5	Fruit, Tree Nuts and Berries
6	Nursery, Greenhouse, Floriculture, and Sod
7	Cut Christmas Trees and Short Rotation Woody Crops
8	Other Crops and Hay

9	Hogs and Pigs
10	Milk and other dairy products from Cows
11	Cattle and Calves
12	Sheep, Goats, and their products
13	Horse, Ponies, Mules, Burros and Donkeys
14	Poultry and Eggs
15	Aquaculture
16	Other Animals and other Animal Products

## Appendix B - Regression Results

**Table 15: Total Government Payments Bi-Variate and Multi-Variable Regressions (All Regression Coefficients)**

Variables	Regression Coefficients					
	(1)	(2)	(3)	(4)	(5)	(6)
Black Farm	-7,394.934*** (307.889)	-5,901.706*** (323.808)	-9,086.101*** (358.510)	-9,824.578*** (357.770)	-8,787.075*** (354.913)	-4,958.789*** (330.101)
Gross Cash Farm Income		5.914*** (0.551)	5.703*** (0.538)		5.533*** (0.543)	5.772*** (0.557)
Female 1 <sup>st</sup> Operator			-4,523.251*** (164.966)	-3,568.697*** (117.226)	-2,817.525*** (130.914)	-2,480.319*** (129.604)
Appalachia Region			-2,690.200*** (124.794)	1,036.036*** (134.759)	1,319.843*** (131.126)	
Southeast Region			3,057.367*** (275.228)	7,357.533*** (281.566)	7,361.219*** (274.834)	
Northeast Region			-2,632.159*** (144.382)	533.688*** (154.072)	1,181.611*** (158.342)	
Lake Region			-3,517.738*** (94.874)	-2,524.605*** (98.994)	-2,255.069*** (98.751)	
Pacific Region			11,061.920*** (596.407)	18,413.120*** (511.083)	15,095.410*** (600.476)	
Delta Region			13,161.540*** (394.416)	16,344.880*** (410.762)	15,826.210*** (399.112)	
Southern Plains Region			6,784.539*** (248.055)	9,652.269*** (257.883)	9,470.874*** (251.201)	
Northern Plains Region			6,639.063*** (144.424)	8,318.280*** (139.441)	7,482.862*** (153.114)	
Mountain Region			10,429.090*** (268.110)	15,162.340*** (262.678)	13,885.690*** (282.228)	

Tobacco				-7,620.708*** (575.428)	-9,465.519*** (563.650)	-10,451.490*** (552.371)
Cotton				20,391.310*** (1,066.011)	18,461.980*** (1,056.256)	22,192.540*** (1,065.938)
Vegetables, Melons, Potatoes, and Sweet Potatoes				-4,456.539*** (624.908)	-8,788.991*** (724.920)	-7,056.699*** (732.712)
Fruit, Tree Nuts, and Berries				-13,548.540*** (482.943)	-13,541.300*** (486.585)	-9,358.919*** (483.404)
Nursery, Greenhouse, Floriculture, and Sod				-10,797.760*** (707.800)	-12,625.700*** (889.594)	-11,133.430*** (641.968)
Cut Christmas Trees and Short Rotation Woody Crops				-14,872.490*** (474.391)	-13,271.500*** (474.139)	-13,763.330*** (424.970)
Other Crops and Hay				-10,256.630*** (127.435)	-8,552.497*** (204.349)	-7,141.295*** (203.435)
Hogs and Pigs				-2,963.868*** (356.589)	-7,426.856*** (557.736)	-9,301.513*** (553.359)
Milk and other dairy products from Cows				-6,621.379*** (195.678)	-12,750.460*** (615.633)	-14,940.490*** (604.611)
Cattle and Calves				-12,131.040*** (152.785)	-11,186.020*** (174.590)	-8,116.903*** (154.564)
Sheep, Goats, and their products				-15,341.280*** (315.984)	-13,623.510*** (346.452)	-11,184.590*** (318.219)
Horse, Ponies, Mules, Burros, and Donkeys				-16,207.100*** (252.716)	-14,169.350*** (312.894)	-11,952.350*** (295.825)
Poultry and Eggs				-10,415.700*** (339.280)	-11,782.510*** (395.379)	-10,161.250*** (370.296)
Aquaculture				-5,876.940** (2,469.655)	-8,241.295*** (2,439.482)	-386.365 (2,447.108)
Other Animals and other Animal Products				-9,104.217*** (94.804)	-9,036.595*** (406.101)	-8,156.658*** (420.620)

Intercept	14,010.800*** (50.179)	12,110.950*** (174.434)	10,165.330*** (175.880)	16,197.890*** (94.804)	14,172.930*** (215.769)	19,372.820*** (525.118)
Number of Observations	1161398	1161398	1161398	1161398	1161398	1161398

Note: Heteroskedastic robust standard errors are reported in parentheses under the coefficient. A Black farm is defined as a farm with at least one operator who is Black or Black and no other race. A White farm is a farm with at least one operator who is White and no other race. The sample used in the regression only includes farms that were either defined as a Black farm or a White farm.

\*\*\*Significant at the 1 percent level.

\*\*Significant at the 5 percent level.

\*Significant at the 10 percent level.