Tariffs, Agricultural Subsidies, and the 2020 US Presidential Election*

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Abstract

This paper provides evidence on the effects of US and Chinese trade policies on the 2020 US presidential election. In response to a series of US tariffs imposed on Chinese goods, China imposed retaliatory tariffs, especially on US agricultural products, which largely affected Republican-leaning counties. The US government then subsidized US farmers by providing direct payments through the Market Facilitation Program (MFP) to mitigate the Chinese retaliatory tariffs. Using the universe of actual county-level MFP disbursement data, we document that MFP payments relative to the Chinese retaliatory tariff exposure were higher in solidly Republican counties, implying that the Trump administration allocated rents in exchange for political patronage. We also find that MFP payments outweighed the estimated impact of Chinese retaliatory tariffs and led to an increase in the Republican vote share in the 2020 presidential election. Finally, we uncover evidence that China's retaliatory trade policy and the corresponding US agricultural policy exacerbated political polarization in the US, especially the rural-urban divide.

Keywords: Agricultural Subsidy, Market Facilitation Program, Political Budget Cycle, Political Polarization, Presidential Election, Tariffs, Trade Policy, Trade War
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1 Introduction

Tariffs and subsidies are long-standing trade policy instruments that governments use to conduct international trade policy. It is also well documented that such trade policies are oftentimes politically motivated such that tariffs and subsidies are granted in response to demands by special interest groups for political patronage (e.g., Mayer 1984; Grossman and Helpman 1994, 1995). In addition, trade policies also commonly trigger a chain reaction – a country uses subsidies and/or countervailing duties in response to another country's trade policies. The recent US-China trade war episode and the subsequent 2020 US presidential election provide a unique opportunity to investigate the political economy of trade protection.

In 2018-2019, the Trump administration imposed a series of tariffs on named trading partners, including China, to reduce the US trade deficit and protect domestic manufacturing jobs. This return to protectionism brought a reaction from China in the form of retaliatory tariffs, especially on US agricultural products, which affected Republican-leaning agriculture-oriented counties most severely (Fajgelbaum et al. 2020; Fajgelbaum and Khandelwal 2021). Those retaliatory tariffs appeared to be aimed at the agricultural regions that were a key part of Trump's political base. In August 2018 the Trump administration went even further and introduced the 2018 Market Facilitation Program (MFP1), which offered direct payments of up to $10 billion to domestic farmers affected by the retaliatory tariffs. As the US-China trade war heated up, the Trump administration made additional direct payments to farmers, as much as $16 billion, through the 2019 Market Facilitation Program (MFP2) in May 2019. Many raised concerns that the MFP1 and MFP2 payments were not fairly distributed across counties and may have been determined by political considerations[1] (Schnitkey, Paulson, Swanson, and Coppess 2019; Janzen and Hendricks 2020; GAO 2020; Balistreri, Zhang, and Beghin 2020; Carter, Dong, and Stein-

[1]"Fairness" mentioned here specifically refers to matching MFP payments to economic damages caused by the Chinese retaliatory tariff shocks.

bach 2020; Adjemian, Smith, and He 2021).

Here we investigate how US voters responded to the US-China trade war and the corresponding US agricultural subsidies in the 2020 US presidential election, as well as whether the distribution of MFP payments was strategically motivated to win the 2020 presidential election. The answers to these questions are of great importance. The (mis)allocation of the US agricultural subsidies to the politically connected could impose substantial economic costs on all US taxpayers, who bear the costs of government-provided subsidies. It is equally important to identify the mechanism by which economic shocks, especially trade and agricultural policies, lead to political outcomes, a challenging issue that is poorly understood (Autor et al. 2020).

We begin by assessing whether the US agricultural subsidies in response to the Chinese retaliatory tariffs were distributed unequally across US counties. To do so, we measure the extent to which US counties were hit by the retaliatory Chinese tariffs per person. We also use the universe of actual county-level disbursements of MFP1 and MFP2 confidential data from the US Department of Agriculture. Using the county-level 2016 presidential election outcome combined with the retaliatory tariff shock and the agricultural subsidy, we document three stylized facts. First, Chinese retaliatory tariffs were more directly targeted at Republican-leaning counties. Second, there was a positive association between the actual disbursements of the MFP and Chinese tariff shocks. Third, Republican-leaning counties received more MFP payments. Our results appear to support our conjecture that the distribution of MFP1 and MFP2 was not equal across counties and that political considerations may have been a factor (GAO 2020; Balistreri, Zhang, and Beghin 2020; Carter, Dong, and Steinbach 2020; Ridley and Devadoss 2022).

However, the positive correlations between Chinese retaliatory tariffs, MFP payments, and the Republican vote share do not necessarily mean that the distribution of the MFP payments was politically motivated. Since agriculturally oriented counties tend to be more heavily Republican, those counties would logically receive more MFP payments, regardless of political orientation. A more meaningful way of evaluating the political considerations that went into the MFP payments would be to calculate a "Net MFP": the difference between the MFP payment and the damage caused by the retaliatory tariffs at the county level. We find that counties more supportive of the Republican Party saw an increase in their Net MFP; and that the amounts of the Net MFP were notably higher in solidly Republican counties. These patterns suggest that the swing voter model (see Lindbeck and Weibull 1987) does not appear to explain the incumbent's strategy in the 2020 presidential election. However, the bigger amounts of the Net MFP in solidly Republican counties appear to support the core voter model (see Cox and McCubbins 1986). This finding implies that the Trump administration allocated rents in exchange for political patronage.

We then analyze how Chinese agricultural trade policy and the US agricultural subsidies all together – that is, the Net MFP – affected the change in Republican vote share between the 2016 and 2020 US presidential elections. We find that the impact of the Net MFP on the Republican share of the two-party (Democratic and Republican) vote is positive. Quantitatively, a one standard deviation increase in exposure to Net MFP is associated with about a 0.38 percentage point increase in the Republican vote share. This result means that the US agricultural subsidies, which were intended to mitigate the Chinese retaliatory tariffs, overcompensated some US voters and led to an increase in the Republican vote share. This is an unintended consequence of China's retaliatory tariffs, whose original purpose was to undermine Trump's political base in exchange for lifting trade restrictions that the US had imposed on China.[2] The result is also robust to alternative construction of the Net MFP, which includes CFAP Payments as an additional component of US agricultural policy.

[2] Fetzer and Schwarz (2021) investigated the degree to which retaliation by the USA's trade partners was politically targeted and documented that retaliatory tariffs were targeted toward areas that supported Trump in the 2016 election. Brutger, Chaudoin, and Kagan (2021) used the concept of politically targeted trade retaliation (PTTR) and found that PTTR, enacted by many countries during the Trump trade war, increased fears of election interference in the US.

Finally, we find evidence that those two trade policies unexpectedly exacerbated political polarization in the US. The implied election effects of the Net MFP were especially high in solidly Republican states and almost negligible in solidly Democratic states, which contributed to increasing partisan polarization. Furthermore, we find evidence of rising rural-urban political polarization. The implied effect of the Net MFP increases monotonically from the most urban area to the most rural area.

This research builds on several recent studies that link international trade with US domestic politics (see Jensen, Quinn, and Weymouth 2016; Che, Lu, Pierce, Schott, and Tao 2016; Blanchard, Bown, and Chor 2019; Autor, Dorn, Hanson, and Majlesi 2020; Lake and Nie 2022; Bombardini, Li, and Trebbi 2020). Our study is complementary but goes one step further in several dimensions.

First, our work provides empirical evidence on the political economy of trade policy (Mayer 1984; Grossman and Helpman 1994, 1995; Goldberg and Maggi 1999; Dutt and Mitra 2005).[3] The research focus in this literature has been to understand how demands for trade protection are mediated through the political process. Exploiting the US-China trade war episode combined with the universe of county-level MFP payments data, we provide unique evidence that the distribution of agricultural subsidies by the incumbent was allocated disproportionately to his supporters for political patronage. Our empirical evidence can thus deepen our understanding of the political economy of trade protection.

Second, our work contributes broadly to the literature on the political budget cycle in which governments manipulate fiscal variables to win elections (Nordhaus 1975; Rogoff and Sibert 1988; Rogoff 1990; Alesina, Roubini, and Cohen 1997). We assess the political economy of the 2020 US presidential election, with a focus on China's retaliatory agricultural tariffs and the US agricultural subsidies. In particular, we show that agricultural subsidies, which were used as countermeasures against China's retaliatory trade policy, can potentially be used as fiscal policy instruments during election periods. In a similar

[3]Trade polices are oftentimes politically motivated in response to demands by special interest groups for political patronage.

vein, some recent studies have found that the distribution of the MFP payments prior to the 2020 presidential election may have been politically motivated (Schnitkey, Paulson, Swanson, and Coppess 2019; Janzen and Hendricks 2020; Balistreri, Zhang, and Beghin 2020; Carter, Dong, and Steinbach 2020). Unlike those studies, we develop a new measure, "Net MFP," to evaluate the political considerations that went into the MFP payments.

Third, our work can shed light on rising political polarization, especially the rural-urban divide, in the United States. Since the 2000 presidential election, the rural vote has become more important for the Republican Party (McKee 2008). In this paper, we provide evidence that rural-urban polarization was exacerbated by China's retaliatory agricultural tariffs and the corresponding US agricultural subsidies (i.e., trade policies) in the 2020 presidential election. Autor et al. (2020) find that rising import competition from China contributed to US polarization.[4] Our finding is in line with their finding that connects adverse economic shocks with political polarization. However, we focus specifically on the rural-urban divide, one type of political polarization that attracts much attention but remains poorly understood, which we attribute to the trade policies (i.e., Chinese retaliatory tariffs and US agricultural subsidies) rather than to Chinese import competition.[5]

Fourth, we investigate the agricultural policy in the context of political economy. There is a long, well-established literature dating back to the late 1980s looking at the political economy of US agricultural policy and congressional voting behavior on agricultural policies. (e.g., Collins 1989; De Gorter and Swinnen 2002; Persson and Tabellini 2002; Anderson, Rausser, and Swinnen 2013; Bellemare and Carnes 2015; Russell 2018; Liu and Kirwan 2020). Previous empirical studies have focused mostly on the politically motivated allocation of agricultural subsidies in the United States (Garrett and Sobel 2003;

[4]Specifically, trade-exposed electoral districts simultaneously exhibited expanding support for both strong-left and strong-right views and shifted toward the Republican candidate in the presidential election.

[5]Admittedly, there are several other factors that might have affected the political polarization in the US, including media bias (DellaVigna and Kaplan 2007), divergence in the ideologies of politicians (Canen, Kendall, and Trebbi 2020), and immigration (Mayda, Peri, and Steingress 2022).

Garrett, Marsh, and Marshall 2006) and in developing countries (Banful 2011; Chang and Zilberman 2014; Mason, Jayne, and Van De Walle 2017). However, there are only a few empirical studies of how agriculture policy affects voting outcomes, especially in the US. Janzen et al. (2021) is one such example. By providing evidence on how agricultural policy affects political outcomes, we contribute to research at the nexus of political economics and agricultural economics.

Last, using the universe of actual disbursement of the US Market Facilitation Program (MFP) confidential data at the county level (the MFP1 in 2018 and the MFP2 in 2019), we develop a novel measure to assess the political economy of trade protection. The MFP data allow us to measure micro-level agricultural subsidies more precisely than previous studies that used estimated MFP1 payments at the county level (e.g., Blanchard, Bown, and Chor 2019; Lake and Nie 2022).[6] Using the actual disbursement dataset, we were able to calculate the Net MFP – the difference between the MFP payment and the damage caused by the retaliatory tariffs at the county level. The Net MFP then allows us to assess the net election effect in one unified framework and to evaluate the political budget cycle in the 2020 presidential election.[7]

The rest of the paper is organized as follows. Section 2 describes the institutional background of the US-China trade war, the Market Facilitation Program, and the US presidential election. Section 3 describes the data sources. Section 4 evaluates whether the Chinese retaliatory tariffs and US agricultural subsidies are politically motivated. Section 5 provides results on how China's retaliatory tariffs and the US agricultural subsidies affected

[6] Janzen and Hendricks (2020) used the actual disbursement of MFP1 obtained from a FOIA request. However, MFP2 (not MFP1) is more likely to be related to political targeting; we use both MFP1 and MFP2 in this paper.

[7] We also improve on previous studies' measurement of the agricultural retaliation tariff shock. For the agricultural retaliation tariff, due to the uniqueness of the agricultural labor market, measuring the tariff shock by relying on employment-based weight may produce measurement errors. For the agricultural industry, the value of production is not necessarily proportional to employment (Fisher and Knutson 2013). We use the county-level market value of agricultural products sold as a weight to better answer our research question in the context of the agricultural sector. Furthermore, we constructed the tariff shock at the product level, not the industry level, and then converted it to the county level. This allows us to capture tariff shocks more precisely than earlier studies.

the 2020 presidential election. Section 6 presents the impacts of Chinese tariffs and US agricultural subsidies on the political polarization in the US. Section 7 concludes.

2 Institutional Background

2.1 The US-China Trade War

We provide a brief summary of the recent US-China trade war beginning in early 2018. We focus specifically on the retaliatory tariffs imposed by China on US agricultural products. Table 1 shows a timeline of the retaliatory tariffs during the US-China trade war.

Table 1: Timeline of China's Agricultural Retaliatory Tariffs

Date	Type	Total Value Impacted	Agricultural Value Impacted	Tariff Shock
4/2/2018	232 Tariffs	$2.4 billion	$0.5 billion	$0.07 billion
7/6/2018	301 Tariffs	$34 billion	$15.6 billion	$3.9 billion
8/23/2018	301 Tariffs	$16 billion		
9/24/2018	301 Tariffs	$60 billion	$0.2 billion	$0.01 billion
6/1/2019	301 Tariffs	$36 billion out of $60 billion	$0.2 billion	$0.01 billion
9/1/2019	301 Tariffs	subset of $75 billion	$12.8 billion	$0.7 billion
2/14/2020	301 Tariffs	subset of $75 billion	Tariffs cut in half (same as above)	-$0.3 billion
Total			$15.8 billion	$4.3 billion

Notes: We use the tariff data in Bown (2020) and the trade value data from the USITC database to calculate the "Agricultural Value Impacted" and "Tariff Shock." Agricultural products refer to goods classified as NAICS 111 and NAICS 112. "Date" refers to the date tariffs were implemented. "Type" indicates the section of the US legislation the tariff corresponds to: (1) Section 301 of the Trade Act of 1974 and (2) Section 232 of the Trade Expansion Act of 1962. "Total Value Impacted" is the total value of US exports to China in 2017 affected by Chinese retaliatory tariffs. "Agricultural Value Impacted" is the total value of US agricultural exports to China, classified as NAICS 111 and 112, in 2017, affected by Chinese retaliatory tariffs. "Tariff Shock" = "Agricultural Value Impacted" $\times$ "Tariff Change."

In March 2018, the US government imposed tariffs on steel and aluminum imports from China under Section 232 of the Trade Act of 1974, which it rationalized with an argument that those imports posed a threat to national security.[8] In April 2018, China

[8] Before the Section 232 tariffs, the first trade barriers imposed early in the Trump administration were global safeguard tariffs on imports of washing machines and solar panels, under Section 201, in January 2018. In response to the safeguard tariffs, in February 2018 the Chinese government launched an antidumping and countervailing duty probe into US exports of sorghum that were worth $1.1 billion in export value to China in 2017. In April 2018, China imposed preliminary anti-dumping tariffs of 178.6 percent on US sorghum. In May 2018, however, China lifted the antidumping and countervailing duty probe into US sorghum imports as the two countries sought to resolve the trade dispute. As a result, Section 201 retaliatory tariffs were not imposed.

imposed retaliatory tariffs on aluminum waste and scrap, pork, fruits and nuts, and other US products worth $2.4 billion in export value in 2017.

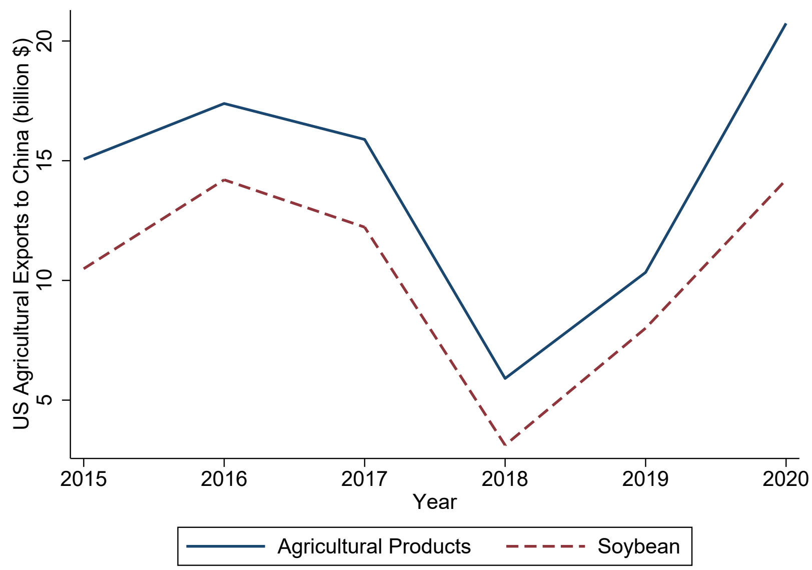
In April 2018, following the conclusion of a Section 301 investigation into whether China was engaging in unfair trade practices, the US government released a $50 billion list of Chinese products under consideration for 25 percent tariffs. The next day, the Chinese government released a $50 billion list of US products under consideration for 25 percent tariffs. They mostly affected US transportation and vegetable products such as soybeans. On July 6, the US and China imposed tariffs on $34 billion of their respective $50 billion lists. On August 23, both the US and China imposed tariffs on the remaining $16 billion of their respective $50 billion lists.

In September 2018, the US imposed a 10 percent tariff on $200 billion in products and China imposed a 5-10 percent tariff on $60 billion in products. In May 2019, the US raised the tariff rate on the Chinese product list from 10 percent to 25 percent. In June 2019, in response to the tariff hike, China also raised its tariff rates on the product list that was already targeted by $36 billion. On September 1, 2019, the US imposed a 15 percent tariff on an additional list of products worth $300 billion. In return, on the same day, China imposed tariffs on an additional product list worth $75 billion. On February 14, 2020, the US cut in half the tariffs of 15% imposed on September 1, 2019; and China cut in half the retaliatory tariffs it had imposed on September 1, 2019.

In January 2020, the US and China reached the so-called Phase One trade deal that eased tensions in the trade war. Although the tariffs remained in place, China agreed to purchase an additional $200 billion in US goods and services over the two next years (2020 and 2021). For agricultural products, China committed to purchase and import no less than $12.5 billion above the 2017 baseline amount in 2020, and no less than $19.5 billion above the 2017 baseline amount in 2021.[9] Further, China agreed to reduce non-tariff barriers that inhibited US exports of agriculture products.

[9]Note that the coverage of agricultural products in the Phase One agreement is broader than the one in our analysis.

Figure 1: U.S. Agricultural Exports to China from 2015 to 2020



Source: Data come from the US Import and Export Merchandise trade statistics, the US Census Bureau.
Note: NAICS codes that fall under 11 (Agriculture, Forestry, Fishing and Hunting) include Crop production (111), Animal production & aquaculture (112), Forestry & logging (113), Fishing, Hunting, & Trapping (114), and Support Activities for Agriculture and Forestry (115). We define agricultural products as those classified in NAICS 111 and NAICS 112, which are fundamentally related to Market Facilitation Program payments.

Figure 1 shows US agricultural exports to China from 2015 and 2020. After the trade war that began in early 2018, US agricultural exports to China dropped from $15.89 billion in 2017 to $5.90 billion in 2018, and slightly recovered to $10.33 billion in 2019. In 2020, exports rebounded again, possibly due to the Phase One agreement, to $20.73 billion.[10]

2.2 Market Facilitation Program

The US is the largest exporter of food and agricultural goods in the world; China is the second-largest importer of US agricultural goods.[11] Hence, during the US-China trade

[10]See Appendix Table A.1 for more detailed export values by commodity.

[11]In 2017, the top two destinations for U.S. agricultural products were Canada (14.9 percent share of US exports) and China (14.1 percent share of US exports). For each product, U.S. export to China by commodity is accounted for 57% of soybean, 80% of sorghum, 17% of cotton, 5% of wheat, 9% of livestock & meat, and 11% of the dairy product. The figures come from the USDA Foreign Agriculture Service-Global Agricultural Trade System Data.

war, China could wield significant power in the agricultural sector (Li, Zhang, and Hart 2018; Janzen and Hendricks 2020). China imposed a series of retaliatory tariffs on agricultural products, as we reviewed in Section 2.1. Trade damages from such retaliation and market distortions reduced agricultural exports to China, especially in 2018 and 2019, and hence financially impacted US farmers (see Figure 1).

In response to the Chinese retaliatory tariffs, the Trump administration authorized the Market Facilitation Program (MFP) to assist farmers in August 2018. The MFP offered direct payments to domestic farmers who were directly affected by the tariffs.[12] The MFP program provided two years of direct payments: (1) MFP1 in 2018 and (2) MFP2 in 2019. In 2018, MFP1 direct payments of $8.6 billion were distributed. As the trade war heated up, the Trump administration increased the direct payments to $14.5 billion through MFP2 for 2019.[13] As of November 2, 2020, $23.1 billion had been distributed to US farming operations.

Table 2 summarizes the MFP1 in 2018 and the MFP2 in 2019. A common feature of both programs is that the trade status of an individual farmer (or legal entity) was not required for application. However, the MFP1 in 2018 differs from the MFP2 in 2019 in significant ways. First, the MFP1 in 2018 applied to nine agricultural commodities.[14] The MFP2 in 2019 expanded the coverage to 34 commodities. Second, USDA increased the payment limit to members of a farming operation from $125,000 to $250,000. Finally, USDA changed the payment structure by changing the MFP base calculation. While the MFP1 was commodity-based, the MFP2 was based on a single county payment rate for non-specialty crops (i.e., all the top export commodities to China, such as corn, soybeans, wheat, and cotton). County payment rates ranged from $15 to $150 per acre, depending

[12]The MFP was established under the statutory authority of the Commodity Credit Corporation (CCC) Charter Act and implemented by the United States Department of Agriculture (USDA) Farm Service Agency (FSA) beginning in September 2018.

[13]The authorized subsidy amounts were up to $10 billion for MFP1 in 2018 and up to $16 billion for MFP2 in 2019.

[14]The nine commodities are cotton, corn, dairy, hogs, sorghum, soybeans, wheat, shelled almonds, and fresh sweet cherries.

Table 2: Description of Market Facilitation Program (MFP) in 2018 and 2019

	MFP1 in 2018	MFP2 in 2019
Authorized subsidy amount	Up to $10 billion	Up to $16 billion
MFP Rates Base	Single rate by commodity	Multiple rates by commodity
County-level rates	Not applicable	Yes for non-specialty crop
County-level rate range	Not applicable	$15-$150 per acre by county
Trade Damage Calculation	Direct export losses	Direct and Indirect export losses
Payment rate base year	2017	2009-2018
# of eligible commodities	9	34
Trade requirement	No	No
Payment limit per farmer	$125,000	$250,000
MFP payment rate ($/unit)		
Soybeans (bushels)	1.65	2.05
Cotton (pounds)	0.06	0.26
Sorghum (bushels)	0.86	1.69
Wheat (bushels)	0.14	0.41
Corn (bushels)	0.01	0.13
MFP formula for non-specialty crop	(Expected trade value - Actual trade value)/(Trade damage)	(Land area)*(County rate per acre)*(Commodity rate)

Source: Data are from the United States Department of Agriculture-Farm Service Agency (USDA-FSA). For the MFP2 Payment rate by county, refer to the following link for details: https://www.farmers.gov/sites/default/files/documents/PaymentRates.pdf
Notes: Eligible individual US farmers or legal entities are required to submit an application to the USDA-FSA to be paid. Trade Damage is defined by the USDA (see USDA 2018, 2019).

on the exposure to trade retaliation in each county, which is determined by the USDA. For the MFP2, the payment rate base year was based on trends in US bilateral trade over a 10-year period (2009-2018), which greatly inflated payments in MFP2 in 2019. Moreover, a trade damage calculation of "indirect export losses" in MFP2 included economic costs associated with adjusting to the disrupted markets, managing surplus commodities, and developing new markets.

Regarding the structural change in MFP payments between 2018 and 2019 by the Trump administration, many raised concerns that the MFP distribution was politically motivated. GAO (2020) noted that big farms in the strongly Republican South disproportionately benefited from MFP. For example, Georgia farmers received the highest average payment per acre in the country, more than twice the national average.[15] In the same vein,

[15]Two articles in the Washington Post in 2019 and 2020 indicated that 9 out of every 10 counties that voted for Donald Trump in 2016 received some support through the program; counties that voted for Hillary

the way in which this procedure was implemented may have "overcompensated" farmers for some crops (Schnitkey, Paulson, Swanson, and Coppess 2019; Janzen and Hendricks 2020). As a consequence, it also overcompensated regions where those crops are grown. Balistreri, Zhang, and Beghin (2020) pointed out that both the 2018 and 2019 MFP payments were concentrated heavily in the Midwestern states, reflecting the political influence of these states' rural communities. They also noted that the burden of tax revenues would fall on all citizens, and thus more populous urban states and urban constituents with more residents. Carter, Dong, and Steinbach (2020) also provides evidence that California farmers were under-compensated in comparison with Midwest and Southern state farmers, saying that the MFP program was mostly about political patronage.

These concerns about the unfair distribution of agricultural subsidies were not something new in history. There are well-established models of the political economy of trade protection (Mayer 1984; Grossman and Helpman 1994, 1995) and their empirical findings (Goldberg and Maggi 1999; Dutt and Mitra 2005). In an investigation of politically motivated agricultural subsidies, Klomp and De Haan (2013) found that public agricultural spending increases before upcoming elections; Park and Jensen (2007) uncovered how agricultural subsidies are systematically tied to political representation in developed countries.

2.3 US Presidential Election

The US presidential election is quadrennial. The 58th presidential election was held on November 8, 2016, and the 59th presidential election was held on November 3, 2020. The US employs the Electoral College, a unique method for indirectly electing the president. In the first stage, when citizens cast their ballots for president in the popular vote, they elect a slate of electors. The number of electors in each state is the same as the state's rep-

Clinton received \$16.68 per person while counties that voted for Trump received \$157.83 per person. One article in the New York Times in 2020 noted that eight of the top nine states–measured by average payments per acre of farmland–were in the South.

resentation in Congress, although each state is entitled to at least three electors regardless of population.[16] In the second stage, the selected electors in each state then directly elect the president and vice president. The candidate who receives an absolute majority of electoral votes, at least 270 out of 538, is eventually elected president.

Historically, the US election has been dominated by two major political parties: the Republican Party and the Democratic Party. Geographically, recent presidential elections have shown that Democrats dominate in the wealthier states in the Northeast and on each coast, and Republicans dominate in the less wealthy states in the middle of the country and the South. Second, while the US presidential election is determined by the Electoral College, the county-level popular vote for the electors in each state is a more precise measure of how voters actually voted. This is because the politics of each county in a state is associated with its economic and demographic characteristics.[17]

Table 3: Presidential Election Results, between 2016 and 2020

Presidential election year	2016		2020	
Party	Republican	Democratic	Republican	Democratic
Presidential nominee	Trump	Clinton	Trump	Biden
Total voter turnout (%)	59.2		66.7	
Popular vote (%)	46.1	48.2	46.9	51.4
Electoral votes (Total=538)	304	227	232	306
Electoral College defectors	2	5	0	0
States carried	30 (+ ME-02)	20 (+ DC)	25 (+ ME-02)	25 (+ DC + NE-02)

Notes: The total voter turnout rate is the percentage of eligible voters who cast a ballot in an election. The popular vote is the percentage of votes cast for a candidate by voters in the 50 states and Washington, D.C. Electoral votes is the number of votes cast by members of the Electoral College. Electoral College defectors are members of the Electoral College who voted for a candidate other than the one to whom they were pledged. ME-02 and NE-02 refer to congressional districts in the states of Maine and Nebraska, respectively. Unlike the 48 other states that use a winner-take-all system, Maine and Nebraska assign votes to the winner in each congressional district.

Table 3 summarizes the US presidential election results in 2016 and 2020. In 2016, the Republican candidate, Donald Trump, defeated the Democratic candidate, former secretary of state Hillary Clinton (304 electoral votes for Trump; 227 electoral votes for

[16]For example, California state has 53 electoral votes (equal to the number of senators (2) plus the number of its representatives in the House of Representatives), while Alaska, Delaware, Washington, D.C., Montana, North Dakota, South Dakota, Vermont, and Wyoming each have three electoral votes.

[17]For example, voters living in rural counties, where the agricultural sector is the primary economic driver, have voted predominantly for Republicans (Gelman et al. 2005).

Clinton). The election was the fifth and most recent presidential election in which the winning candidate lost the popular vote (46.1% for Trump; 48.2% for Clinton). In 2020, Democrat Joe Biden defeated the Republican incumbent, Donald Trump (306 electoral votes for Biden; 232 electoral votes for Trump). Although Biden won the larger share of the popular vote against Trump, Trump's popular vote rose by 0.8 percentage points from 46.1% in 2016 to 46.9% in 2020.

Although there were a number of important issues in 2016, including foreign policy and health care, the economy was the top issue in the 2016 presidential election. Economic concerns in the Rust Belt, which contains the populous swing states of Michigan, Ohio, Pennsylvania, and Wisconsin, were an important topic in the presidential debates in 2016, and those states were decisive in Trump's 2016 win. In the 2020 presidential election, however, the COVID-19 pandemic crisis brought health care and unemployment to the fore for voters. The US-China trade war and racial justice issues also shaped the 2020 election.

Among the several issues brought up in the 2020 presidential election, the US-China trade war was not unilaterally favorable to one party. The Trump administration pursued a protectionist trade policy by imposing tariffs on foreign products, especially targeting China in early 2018. Potentially, the Trump administration may have benefited from his trade policy and "America First" campaign slogan. But China's retaliatory tariffs, especially on agricultural products, were widely viewed as a negative by the Republican Party because those rural areas were strong supporters of Trump in 2016 (Fetzer and Schwarz 2021; Bown 2020; Fajgelbaum, Goldberg, Kennedy, and Khandelwal 2020). In response to the retaliatory tariffs, the Trump administration provided subsidies to US farmers, possibly offsetting the anti-Trump effect of the retaliatory tariffs and perhaps even attracting more voters in red states (Carter, Dong, and Steinbach 2020; Lake and Nie 2022).

3 Data Overview

In our empirical analysis of presidential elections, we examine county-level changes between 2016 and 2020 in the Republican candidate's share of the two-party (Democratic and Republican) vote. We relate them to county-level measures of the shock from China's retaliatory tariffs and county-level US agricultural subsidies during the same period.[18]

3.1 US Presidential Elections

Our voting data on the US presidential election come from David Leip's Election Atlas. We use the data on voting results at the county level for the 2012, 2016, and 2020 US presidential elections.[19] The data include county-level votes for each candidate from the Republican and Democratic Parties as well as third-party candidates. Following the previous literature (Blanchard, Bown, and Chor 2019; Autor et al. 2020), we compute the Republican candidate's share of the two-party vote, which is defined as the number of Republican votes divided by the total votes for the Republican and Democratic candidates (hereafter "Republican vote share").[20]

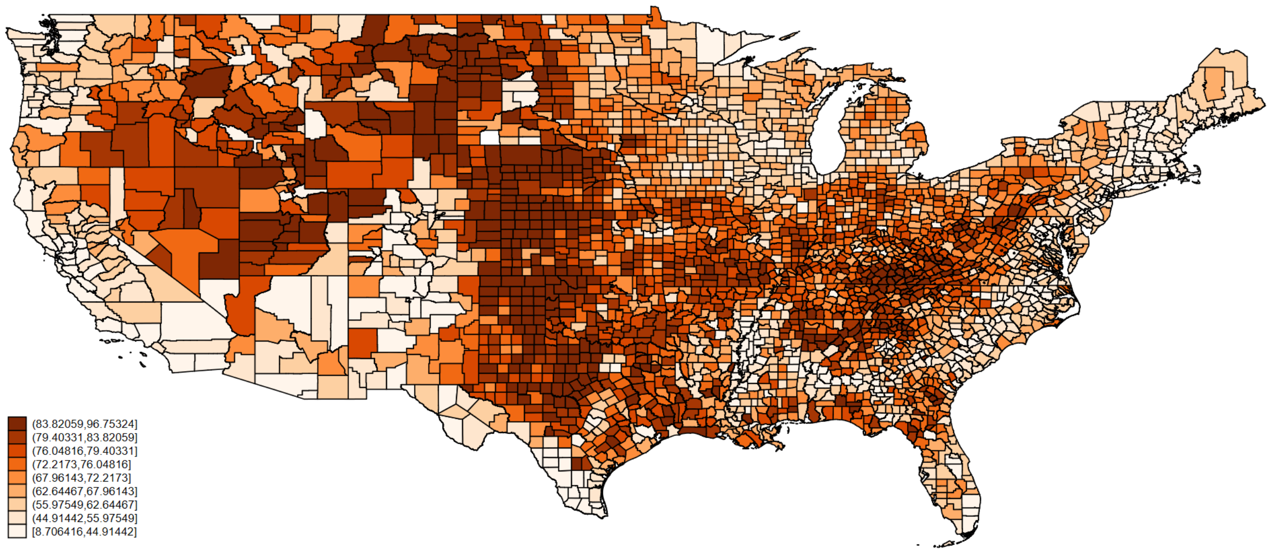
Figure 2 shows the county variation in the Republican vote share in 2016. In this map, a county is colored according to its position within the distribution. A darker orange indicates that a county frequently supports Republicans; a lighter orange indicates that a county frequently supports Democrats. Rural counties (or suburban counties) in the middle of the country and the South largely supported the Republican Party while urban

[18]Our unit of analysis is the county, an administrative subdivision of a state that consists of a geographic region with specific boundaries. As of 2020, there are 3,243 counties, including 236 county-equivalents and the District of Columbia. We exclude 100 county-equivalents in the territories (such as Puerto Rico) outside the 50 states. We further exclude 30 Alaska counties and 1 county in Hawaii in which county-level tallies do not exist. Our final sample includes 3,112 US counties.

[19]For this study, we use version 0.7, which contains the most recent election results as of December 10, 2020.

[20]Since US county FIPS codes have changed over time, we manually match the county FIPS codes for the year 2016. For example, Shannon County, South Dakota, (46113) was changed to Oglala Lakota County, South Dakota (46102) on May 1, 2015. The Independent city of Bedford, Virginia (51515) became part of Bedford County, Virginia (51019) on July 1, 2013.

Figure 2: Republican Share of the Two-Party Vote in the 2016 Presidential Election (%)



counties in the Northeast and the West were more inclined to vote for the Democratic Party.

Panel A of Table 4 presents summary statistics on voting outcomes. On average, the Republican vote share declined by 0.55 percentage points between 2016 (66.66%) and 2020 (66.11%). There is a substantial variation across counties in which the smallest change was a decrease of 8.08 percentage points and the largest change was an increase of 28.16 percentage points. One standard deviation is 2.58 percentage points.

3.2 Agricultural Tariff Shocks

We measure the county-level Chinese agricultural retaliatory tariff exposure per person as follows:

$$Chn\_Ag\_TS_c = \frac{1}{L_c} \sum_{p \in P^{Ag}} \frac{V_{pc}}{V_p} \times TS_p^{US \to CHN} \tag{1}$$

Table 4: Summary Statistics (Key Variables)

Variables	Mean	SD	Min	Max	Format
Panel A. Voting Outcomes					
Δ *Rep. Vote Share (2020 - 2016)*	-0.55	2.58	-8.08	28.16	Δ Percent
Δ *Rep. Vote Share (2016 - 2012)*	5.88	5.21	-16.52	24.29	Δ Percent
Rep. Vote Share (2020)	66.11	16.31	5.53	96.89	Percent
Rep. Vote Share (2016)	66.66	16.16	4.30	96.75	Percent
Rep. Vote Share (2012)	60.77	15.04	6.02	96.53	Percent
Panel B. China's Ag. Ret. Tariff Shocks					
China's Ag. Ret. Tariff Shock	1,284,263	2,043,950	0	17,003,974	US$
China's Ag. Ret. Tariff Shock per person	104	243	0	2,647	US$
Panel C. Agricultural Subsidies					
MFP	7,414,081	11,393,056	0	80,672,686	US$
MFP per person	619	1,387	0	15,424	US$
Panel D. Net MFP					
Net MFP	4,845,555	7,658,921	-2,452,505	65,378,648	US$
Net MFP per person	412	938	-1,033	10,378	US$

Note: N = 3,112 counties for 49 out of 50 US states. Alaska is excluded because county-level election results are not officially reported. All variables are reported at the county level. Voting outcomes in Panel A are from David Leip's Election Atlas Presidential Data version 0.7. The Republican vote share is the number of votes for the Republican candidate out of the total votes cast for the Democrat and Republican candidates at the county level. "China's Ret. Ag. Tariff Shock" is China's Retaliatory Agricultural Tariff Shock. "MFP" is Market Facilitation Program payments that include the sum of MFP1 in 2018 and MFP2 in 2019. "Net MFP" is defined as the difference between an MFP payment and two times the Chinese retaliatory agricultural tariff shock, Net $\text{MFP}_c \equiv \text{MFP}_c - 2 \times \text{Chn\_Ag\_TS}_c$.

where c refers to a county, p denotes an HS 6-digit product, and P^{Ag} is the set of agricultural products.[21] V_{pc} denotes the market value of agricultural product p and county c; V_p denotes the total market value of agricultural product p in the US; $TS_p^{US \to CHN}$ means the China's retaliatory tariff shock that falls on product p; and L_c denotes the total population in county c. The data on the market value of agricultural products come from the 2017 Census of Agriculture. The tariff shock data are sourced from Bown (2020) and the USITC database. The population data come from the US Census.

China's retaliatory tariff shock that falls on HS 6-digit product p, $TS_p^{US \to CHN}$ was constructed as follows. First, we use the information on China's agricultural retaliatory tariffs

[21]The county-level Chinese agricultural retaliatory tariff exposure per person attempts to estimate the *true* economic damages of retaliatory tariffs at the county level. Admittedly, unlike the disbursement of MFP payments, measuring the *true* economic damages of retaliatory tariffs at the county level is difficult because economic actors in different counties could respond differently to the imposition of tariffs. Despite this limitation, we believe that our county-level measure substantially enhances the earlier measures, given the available datasets.

collected by Bown (2020).[22] Let $\Delta(\tau_p^{US\to CHN})$ denote the retaliatory tariff rate increase on US exports to China in product p. Second, the HS-6-digit trade data come from the USITC database in 2017. Let $X_p^{US\to CHN}$ be the value of trade flows for product p from the US to China in 2017. Last, let $TS_p^{US\to CHN} = X_p^{US\to CHN} \times \Delta(\tau_p^{US\to CHN})$ be the magnitude of tariff revenues that would be raised holding trade flows constant in 2017.

In practice, we choose five major crops to measure the county-level Chinese agricultural retaliatory tariff exposure per person: soybean (HS code: 120190), cotton (520100), sorghum (100790), hay (121490), and wheat (100199). Unlike the more aggregated unit (i.e., the county-level market value of the agricultural industry, NAICS 111), there are numerous missing values for the market value of products at the county level due to the requirement to avoid disclosing data for individual operations. The major five crops accounted for 92.6 percent of the total agricultural Chinese retaliatory tariff shock (i.e., \$4.0 billion out of \$4.3 billion).[23]

We adopt the county-level measure of China's retaliatory tariff exposure per worker used in Blanchard, Bown, and Chor (2019), but we modified significantly their measure in order to answer our research question in the context of the agricultural sector. First, our unit of analysis is the HS-6-digit product (then converted to the county level), rather than the NAICS 3-digit industry in Blanchard, Bown, and Chor (2019). Within the agricultural industry (i.e., NAICS 111), some crops, such as soybeans, are more affected by the Chinese retaliation than other crops. Thus, using the county share of the value of production for a given industry (i.e., $\frac{V_{ic}}{V_i}$ where i denotes a NAICS 3-digit industry) will involve measurement errors for a county's exposure to the tariff shock.

Second, we use the county-level market value of agricultural products sold as a weight

[22] In Table 1, we provided a timeline of China's agricultural retaliatory tariffs.

[23] One may argue that commodities might respond differently to the trade war. To put it another way, a certain commodity can absorb the negative shock by diverting their export destinations more easily than other commodities. If so, the county-level Chinese agricultural retaliatory tariff exposure per person in equation 1 may over- or under-estimate the true tariff shock. However, a single commodity (i.e., soybean) accounted for 77.5 percent of the total agricultural Chinese retaliatory tariff shock as of 2017. Thus, cross-commodity variations would be less concern for our context.

rather than using an employment weight at the county level. Because of the uniqueness of the agricultural labor market, measuring tariff shock by relying on employment-based weight is likely to produce measurement errors. For the agricultural industry (or product), the value of production is not necessarily proportional to employment (Fisher and Knutson 2013).[24] To overcome this issue, we adopt the county-level market value of agricultural products sold in 2017 to weight the county-level contribution of each agricultural product, using the 2017 Census of Agriculture data developed by the USDA National Agricultural Statistics Service.[25]

One could argue that $TS_p^{US \rightarrow CHN}$ in equation (1) overestimates the true impact of the tariff because US prices would not have fallen (possibly due to trade diversion to other destinations). However, Carter and Steinbach (2020) argue that the decrease in trade with retaliating countries was not fully compensated for the gain in trade with non-retaliating countries. Further, Cavallo et al. (2021) found that during the US-China trade war US exporters dropped their (pre-tariff) prices by about 5 percent in response to retaliatory tariffs that averaged about 15 percent. They further found that the decline in the relative export price of retaliated-upon products was almost entirely driven by US shipments of non-differentiated and agricultural goods to China. Their core results hence support the conclusion that the tariff shock was not fully borne by Chinese importers.

[24]For example, within the agricultural industry (i.e., NAICS 111), specialty crop production is more labor-intensive but less impacted by the Chinese agricultural tariff shock. However, non-specialty crops, such as soybeans, are less labor-intensive but more affected by the Chinese retaliation. Also, given the nature of agricultural production, most field crop labor is employed seasonally. The seasonality of the agricultural labor market often overestimates the actual employment by labor-intensive commodity farms.

[25]The 2017 Census of Agriculture collected by the USDA National Agricultural Statistics Service is a complete count of US farms and ranches, even small plots of land, if $1,000 or more of products were sold during the Census year. Unlike the CBP data, the 2017 Census of Agricultural data allows us to capture the market value of agricultural product p and county c. As noted in Blanchard, Bown, and Chor (2019), the CBP data are incomplete for agriculture. The CBP data do not even provide employment data for NAICS 111 (Crop Production) and NAICS 112 (Animal Production and Aquaculture). Blanchard, Bown, and Chor (2019) used "Support Activities for Agriculture and Forestry (NAICS 1151, 1152)" as proxies for "Crop Production (NAICS 111)" and "Animal Production and Aquaculture (NAICS 112)", respectively. Further, for confidentiality reasons, for numerous observations the data use a letter code to indicate the range within which the actual value lies, so-called "class flags", that make it difficult to capture precise employment levels, particularly, at the county level. Because the 2017 Census of Agriculture data has fewer class flags, we are able to measure county-level production more precisely.

Figure 3: China's Agricultural Retaliatory Tariff Shock per Person ($)

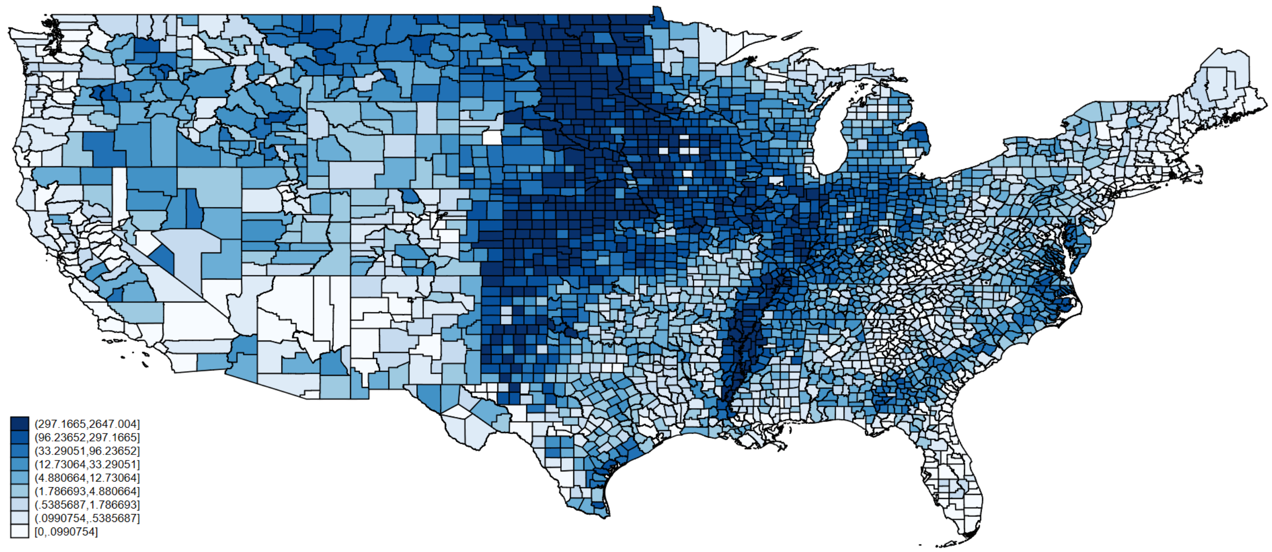


Figure 3 shows the county variation in the shock caused by China's retaliatory tariffs per person. A darker blue indicates a county with a high tariff shock; a lighter blue indicates a county with a lower tariff shock. Agricultural counties in the Mississippi River Basin and the Southeast appear to have been hit hard by China's retaliatory tariffs.

Panel B of Table 4 presents summary statistics on agricultural tariff shocks. On average, China's agricultural retaliatory tariff shock per person at the county level is $104. There is substantial variation across counties: the lowest is zero and the highest is $2,647. The standard deviation is $243. In 101 counties (out of 3,112 counties) there was no retaliatory tariff shock.

3.3 US Agricultural Subsidies

Our county-level measure of the agricultural subsidy is from the USDA Farm Service Agency (USDA-FSA). We use the actual disbursement of Market Facilitation Program (MFP) data at the county level.[26] The total actual disbursement of MFP1 in 2018 and

[26] Permission to access the data was granted through an official arrangement between the authors and the USDA-FSA. More specifically, the data we used in the paper was accessed through the Freedom of Information Act (FOIA) request dated October 20, 2020, along with the control number 2021-FSA-00445-F by the US Department of Agriculture.

MFP2 in 2019 was $23.1 billion. The MFP payments were distributed over three years – $5.2 billion in 2018, $14.2 billion in 2019, and $3.7 billion in 2020.

This study complements previous studies that used estimated, not actual, MFP payments at the county level (i.e., Blanchard, Bown, and Chor 2019; Lake and Nie 2022). In those studies, an MFP payment at the county level is estimated by combining information on the subsidy rates by commodity based on the MFP1 in 2018 and county-crop output data from 2017.[27] Adopting the estimated agricultural subsidy variable directly from Blanchard, Bown, and Chor (2019) may generate measurement errors, especially in a study of the 2020 presidential election.[28] First, as we discussed in 2.2, between 2018 and 2019 the MFP rate base, covered crops, and thus the calculation of MFP changed. For example, MFP2 in 2019 for non-specialty crops is based on a single-county payment rate multiplied by a farm's total plantings of MFP-eligible crops.[29] Second, the MFP payments are provided only for eligible applicants, who must satisfy legal conditions established by the USDA-FSA.[30] Last, some data are missing from estimations using county-level crop outputs. Unlike large commodities such as soybeans, corn, and cotton, numerous small commodities/agricultural products are not often reported at the county level annually.[31]

Using the actual disbursement data at the county level, Figure 4 shows the county

[27] Blanchard, Bown, and Chor (2019) estimate the total MFP1 payment by county by combining the following information: (i) MFP1 subsidy rates by commodities announced by the Congressional Research Service report and (ii) the county-level agricultural production by commodity in the year 2017 from the US Department of Agriculture's National Agricultural Statistics Service. Due to the data limitations, the estimation by Blanchard, Bown, and Chor (2019) used production data in 2012 for hogs and omits two specialty crops (Fresh sweet cherries and Shelled almonds).

[28] Blanchard, Bown, and Chor (2019) study the 2018 congressional election and hence the MFP2 in 2019 is not related to their study. Note also that there was a structural change in MFP payment between 2018 (MFP1) and 2019 (MFP2). Lake and Nie (2022) directly borrowed the agricultural subsidy measure in Blanchard, Bown, and Chor (2019) and investigate the 2020 Presidential election, but their main focus is not on agricultural subsidy.

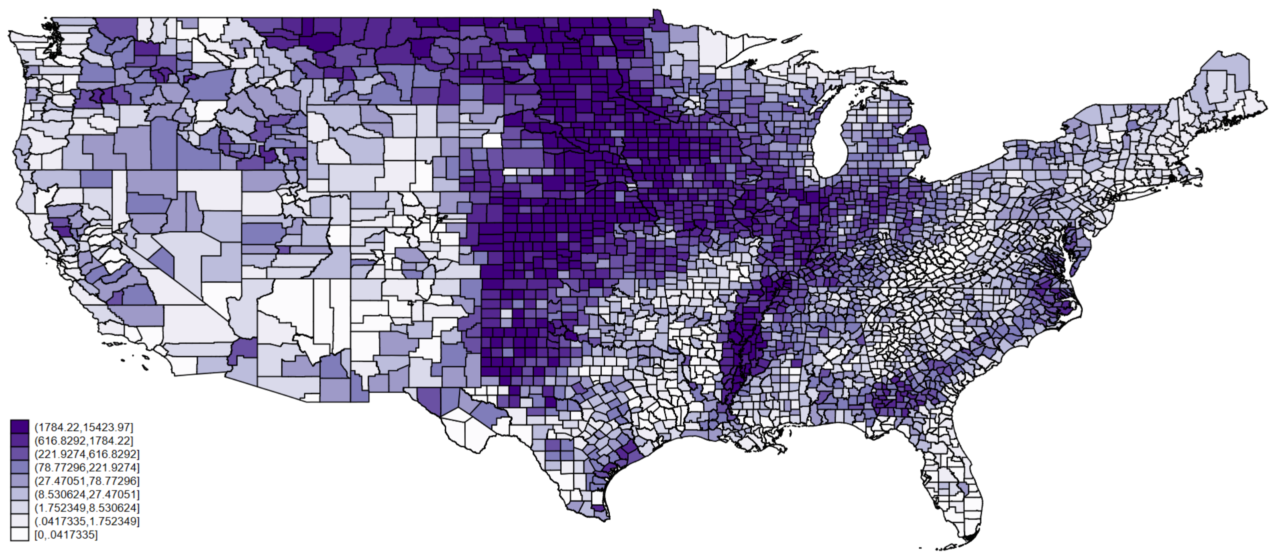
[29] A producer's total payment-eligible plantings are not allowed to exceed total plantings in the previous year. Also, MFP2 payments are limited to a combined $250,000 for non-specialty crops per legal entity, $250,000 for dairy and hog producer, and specialty crop producers.

[30] To be eligible for payments, a farming operation must either have an average adjusted gross income of less than $900,000 for tax years 2015, 2016, and 2017 or derive at least 75 percent of its adjusted gross income from farming or ranching. Refer to the following link for more details: https://www.farmers.gov.

[31] The measurement error is likely to occur by using alternative years of production data to replace missing data for those agricultural products.

variation in the MFP payments per person. A darker purple indicates that a county received more MFP payments; a lighter purple indicates that a county received very few MFP payments. Agricultural counties in the Midwest and South, which generally support the Republican Party, appear to have received more MFP payments than other US regions.[32]

Figure 4: Market Facilitation Program Subsidies per Person ($)



Panel C of Table 4 presents summary statistics on agricultural subsidies. On average, an MFP payment per person at the county level is $619. There is substantial variation across counties: from zero subsidies to $15,424. The standard deviation is $1,387. There are 290 counties (out of 3,112 counties) that receive zero MFP payments.

3.4 Control Variables

Following the previous literature on determinants of presidential elections, we include an extensive set of county-level control variables. Most of the control variables are from the American Community Survey (ACS) developed by the US Census Bureau, which com-

[32]There exists a significant imbalance between the Republican counties and Democratic counties. Using presidential voting statistics from the 2016 election, we find that the average MFP payment per person is four times larger in Republican-dominated counties ($702) than in Democratic-dominated counties ($174).

piles county-level industry, socioeconomic, and demographic characteristics. We use the ACS 5-year estimates from 2012 and 2016 to construct county controls for 2016 and for changes (between 2012 and 2016).[33] The COVID-19 related variables, such as the incidence of cases and deaths, stay-at-home orders, and public mask mandates, come from the Centers for Disease Control and Prevention (CDC) and Covid Act Now (CAN).[34] We also use the Armed Conflict Location & Event Data Project (ACLED) dataset to control for the Black Lives Matter (BLM) movement.[35]

Appendix Tables A.2 and A.3 present the summary statistics for these county controls. In Panel A (of both tables), we include county-level sectoral employment share, which breaks county-level employment down by sector (i.e., "agricultural & mining" and "manufacturing") to control for industry characteristics. In Panel B (of both tables), we include the distribution of household annual income by eight-income bins, (log) median and mean household annual incomes, labor force participation rate, and the unemployment rate to control for economic characteristics at the county level. In Panel C (of both tables), we control for county-level demographic characteristics by including population share by four education levels, gender, four races, seven age bins, voting age, and health insurance coverage rate, all at the county level. In Panel D of Appendix Table A.2, we control for COVID-19 by including county-level cumulative deaths (and cases) per 1,000 population as of November 2, 2020, one day before Election Day. We also include county-level stay-at-home orders (and public mask mandates, respectively) by counting the number of days from April 10, 2020, to November 2, 2020 (and from March 15, 2020, to May 5, 2020, respectively) that a county imposed stay-at-home orders (and public mask mandates, respectively). In Panel E of Appendix Table A.2, we control for the Black Lives Matter (BLM) movement by including the number of demonstrations associated with the

[33]The 5-year estimates allow us to observe statistically reliable data for less populated counties and small population subgroups. ACS provides a non-overlapping dataset. Refer to the following link for more details: https://www.census.gov/programs-surveys/acs/about/acs-and-census.html

[34]Refer to the following link for more details: https://covidcountydata.org/

[35]ACLED collects the dates, actors, locations, fatalities, and types of all reported political violence and protest events around the world.

BLM movement at the county level for the period between May 25, 2020 (the day of the death of George Floyd) and November 2, 2020 (one day before the presidential election).

4 Tariffs, Subsidies, and Political Targeting

Before proceeding to our core empirical analysis, in Section 4.1 we conduct a correlation analysis of whether Chinese tariff retaliation, US agricultural subsidies, and the Republican vote share in 2016 were associated with each other at the county level. In Section 4.2 we examine whether the US agricultural subsidies relative to the Chinese retaliatory tariffs were disproportionately distributed across US counties in the context of the political budget cycle (Rogoff and Sibert 1988; Rogoff 1990; Alesina, Roubini, and Cohen 1997).

4.1 Correlation Analysis

We first analyze whether Republican-leaning counties were more targeted by Chinese retaliatory tariffs on agricultural products by correlation analysis using all counties as follows:

$$Chn\_Ag\_TS_c = \beta RV_c^{2016} + \psi_s + \varepsilon_c \tag{2}$$

where c denotes a county and s indicates state. Chn_Ag_TS_c is the Chinese agricultural retaliatory tariff shock for county c measured in dollars per person. RV_c^{2016} is the Republican vote share in the 2016 presidential election in county c. ψ_s is state fixed effects. We weight counties by total voting age-population in 2016.

In column (1) of Table 5, a one percentage point increase in Republican vote share is associated with an increase in the Chinese agricultural tariff shock of 0.76 dollars per person. In column (2) of Table 5, we include state fixed effects. The coefficient is 0.68, suggesting that Republican-leaning counties seemed to be targeted by Chinese agricultural trade policy.[36]

[36] This result is consistent with recent findings by Fetzer and Schwarz (2021), Fajgelbaum et al. (2020),

Table 5: Retaliatory Tariff Shocks and Republican Vote Share in the 2016 Election

Dependent Variable:	Chinese Ag. Tariff Shock		Market Facilitation Program			
	(1)	(2)	(3)	(4)	(5)	(6)
Rep. Vote Share (2016)	0.7612***	0.6808***			4.4381***	4.1510***
	(0.1862)	(0.2269)			(1.0564)	(1.2474)
Chinese Ag. Tariff Shock			5.4265***	5.3703***		
			(0.1775)	(0.1884)		
State FEs	No	Yes	No	Yes	No	Yes
Observations	3,112	3,111	3,112	3,111	3,112	3,111
R-squared	0.0459	0.2211	0.9229	0.9262	0.0489	0.2290

Note: In columns (1) and (2), the dependent variable is Chinese Agricultural Retaliatory Tariff Shock for county c measured in dollars per person. In columns (3) to (6), the dependent variable is the Market Facilitation Program payment for county c measured in dollars per person. Observations are weighted by the total voting-age population in 2016. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

In response to the retaliatory tariff shocks, the US government announced a Market Facilitation Program (MFP) to subsidize US farmers. We estimate the following equation to study the relationship between the tariff shock and MFP.

$$MFP_c = \beta Chn\_Ag\_TS_c + \psi_s + \varepsilon_c \tag{3}$$

where MFP_c measures actual disbursements of MFP payments.

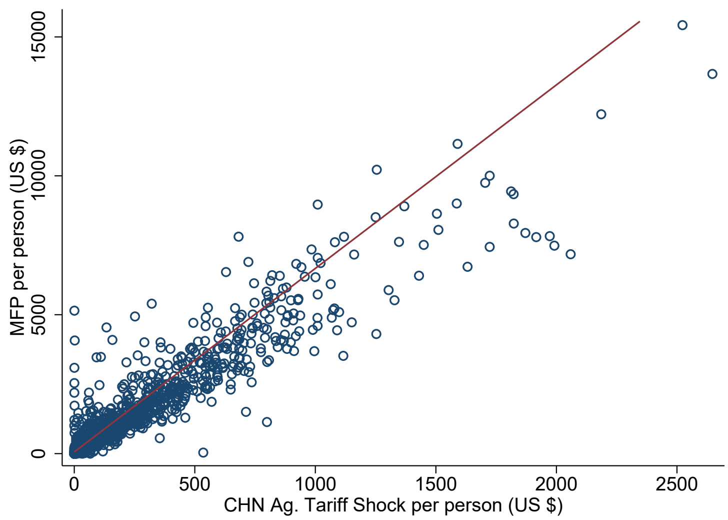
In column (3) of Table 5, a one dollar per person increase in the Chinese agricultural tariff shock is associated with an MFP payment increase of 5.43 dollars per person. In column (4) of Table 5, we include state fixed effects and found the coefficient to be 5.37.

Figure 5 further depicts the positive association between the MFP and the Chinese agricultural tariff shock. Since the MFP was intended to mitigate the negative consequences of retaliatory tariff shocks, the positive association is an expected outcome. However, there are two additional patterns from the correlation analysis and the scatter plot that are worth mentioning. In Figure 5, conditional on the same magnitude of the tariff shock, counties receive different levels of MFP payments. This suggests that some coun-

and Kim and Margalit (2021) where those papers noted that tariff retaliation was directly targeted to areas that swung to Donald Trump in 2016.

ties received MFP payments that were larger than the tariff shock and vice versa.[37]

Figure 5: Market Facilitation Program and Chinese Agricultural Tariff Shock



Note: The figure shows a scatter plot and a linear fit between MFP per person and Chinese agricultural tariff shock per person.

To the extent that tariff shocks are positively correlated with MFP subsidies, we would also expect that Republican-leaning counties attracted more MFP subsidies.[38] We conduct the following correlation analysis to study the relationship between MFP subsidies and the Republican vote share in 2016:

$$MFP_c = \beta RV_c^{2016} + \psi_s + \varepsilon_c \tag{4}$$

In column (5) of Table 5, a one percentage point increase in Republican vote share is associated with an increase in MFP payments of 4.44 dollars per person. In column (6) of Table 5, after controlling for state fixed effects, the coefficient is 4.15.

[37]Since we can interpret the difference between the MFP payment and the tariff shock at the county level as the result of the two trade policies combined (i.e., Chinese agricultural tariffs and US agricultural subsidies), the county-level variations in the two trade policies will allow us to assess the their overall impact on the 2020 presidential election in Section 5.

[38]Our expectation is based on the political economy of trade protection (Mayer 1984; Grossman and Helpman 1994, 1995) where political decisions on trade protection policies are reflections of the selfish economic interests of voters.

In short, Chinese agricultural retaliatory tariffs appear to target Republican-leaning agricultural counties, resulting in more US agricultural subsidies in those counties. We interpret the relations among the three variables as positive correlations. Hence, in assessing the impact of both trade policies on the 2020 presidential election in Section 5, it appears to be essential to control for the Republican vote share in 2016.

4.2 The Net Market Facilitation Program

The positive association between Chinese retaliatory tariffs, MFP payments, and Republican vote share do not necessarily mean that the distribution of the MFP payments was politically motivated to win the 2020 presidential election. Since agricultural counties tend to lean Republican, it seems natural that those counties received more MFP payments, regardless of political orientation. We therefore develop a new measure–Net MFP–which is the difference between the MFP payment and the damage caused by the Chinese agricultural retaliatory tariff at the county level, to assess the political economy of the 2020 presidential election.[39]

For each county c, "Net MFP" is calculated as the difference between an MFP payment and an adjusted Chinese agricultural retaliatory tariff as follows:

$$NetMFP_c \equiv MFP_c - \kappa \times Chn\_Ag\_TS_c \tag{5}$$

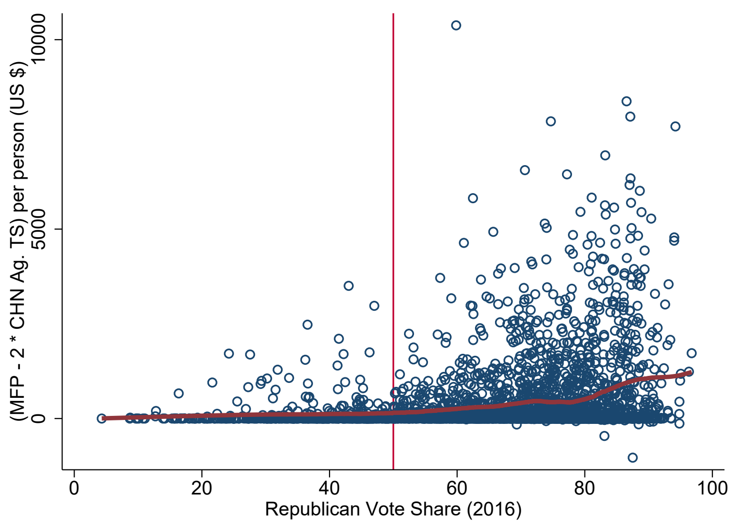
where $\kappa > 0$. The above measure captures the combined trade policies (Chinese retaliatory tariff and US agricultural subsidy) at the county level because MFP was specifically designed to mitigate the negative consequences of agricultural retaliatory tariffs (USDA 2018). In order to capture the damages from the Chinese retaliatory tariff shock, we adjust the magnitude of $Chn\_Ag\_TS_c$ by multiplying a real number, $\kappa > 0$, that ensures that the

[39] Janzen and Hendricks (2020) compared the impacts of MFP payments and the retaliatory tariffs at the product level. In this vein, the reason for comparing MFP payments and retaliatory tariffs looks quite similar. However, more precisely, our Net MFP measure is at the county level, which enables us to investigate the political economy of trade protection.

Chinese retaliatory tariff shock is comparable to MFP.[40]

As a baseline, we set κ as 2 because the time span between the initial imposition of tariffs and the 2020 presidential election is about 2 years, mainly in the period of 2018 and 2019.[41] As China committed to purchasing agricultural products worth \$12.5 billion in 2020 and \$19.5 billion in 2021, under the Phase One agreement in January 2020, there is increasing evidence that negative impact of the Chinese agricultural tariff shock declined, especially in the agricultural sector (see Figure 1).[42]

Figure 6: (MFP $-2\times$ Chinese Ag. Tariff Shock) and Republican Vote Share (2016)



Note: The vertical axis represents Net MFP; the horizontal axis represents the Republican vote share in 2016. We perform a locally weighted regression of "Net MFP" on the Republican vote share in 2016 and plot a lowess smoother. The figure displays a scatter plot between "MFP $-2\times$ Chinese Ag. Tariff Shock" and Republican vote share in 2016. The red curve shows a lowess smoother with a bandwidth equal to 0.8.

We first check whether our new measure is correlated with the Republican vote share in 2016 across US counties. Figure 6 summarizes the relationship. Interestingly, counties

[40]Note that the magnitude of $Chn\_Ag\_TS_c$ is based on the magnitude of tariff revenues that would be raised holding trade flows constant from 2017 (i.e., annual values).

[41]Admittedly, as discussed in Section 3.2, measuring the true economic damages of retaliatory tariffs at the county level is a difficult task. Nevertheless, we believe that our measure here significantly improves on the previous measures.

[42]Panel D of Table 4 presents summary statistics for Net MFP. On average, Net MFP at the county level is \$412. There is substantial variation across counties: the lowest is -\$1,033 and the highest is \$10,378. The standard deviation is \$938.

more supportive of the Republican Party saw an increase in the Net MFP, which suggests that the distribution of MFP payments between red counties and blue counties was not equal given the same level of Chinese tariff exposure. Since MFP provides assistance to US farmers with commodities directly impacted by foreign retaliatory tariffs, there would be no reason for different patterns between the two unless there were political motivations.[43]

Does this result mean the distribution of MFP payments was strategically motivated to win the 2020 presidential election? Or does this result indicate that the Trump administration allocated rents in exchange for political patronage? Cox and McCubbins (1986) argue that politicians will adopt strategies in which they invest little (if at all) in opposition groups, somewhat more in swing groups, and more still in their support groups; researchers call this strategy the "core voter model." The US election system is nevertheless a winner-take-all system, wherein the ticket that wins a plurality of votes wins all of that state's allocated electoral votes. Therefore if the incumbent had strategically distributed MFP payments to win the 2020 presidential election, one would expect the effect to have been higher in swing states. Lindbeck and Weibull (1987) propose that parties target policy benefits to ideologically neutral voters since the marginal utility of consumption is decreasing, and per capita transfer to a group is a decreasing function of the absolute value of the expected party bias in the group; researchers call this strategy the "swing voter model."

Based on these two competing models combined with the pattern in Figure 6, the swing voter model does not appear to explain the incumbent's strategy in the 2020 pres-

[43] As we discussed in Section 2.2, many raised concerns about the unequal distribution of the MFP payments (Schnitkey, Paulson, Swanson, and Coppess 2019; Janzen and Hendricks 2020; GAO 2020; Balistreri, Zhang, and Beghin 2020; Carter, Dong, and Steinbach 2020). We think that our measure of the Net MFP, not the MFP payments themselves, extends previous studies that assess the political considerations of the MFP payments in several dimensions. First, we demonstrate that Republican counties are more agriculturally oriented, and hence it seems natural that those counties received more MFP payments, regardless of political orientation. Whether the MFP payments were politically distributed or not should be evaluated according to the Net MFP that we define in equation (5). Second, our analysis is based on all US counties, while previous studies conducted state-level (and some county-level) analyses. Third, we use the actual disbursements of MFP payments, while previous studies used estimated MFP payments.

idential election. However, the increasing Net MFP pattern (captured by the lowess smoother) appears to support the core voter model, implying that the Trump administration allocated rents in exchange for political patronage.

5 Tariffs, Subsidies, and the 2020 US Presidential Election

In the previous pages we evaluated the impact of Chinese tariffs, as well as US agricultural subsidies, on US counties and documented that both trade policies were to some extent politically targeted. In Section 5.1, we examine how Chinese agricultural trade policy and US agricultural subsidies together affected the 2020 US presidential election. In Section 5.2, we then subject our results to a robustness test that includes CFAP Payments, a component of US agricultural policy.

5.1 Did Chinese Tariffs and US Subsidies Affect the 2020 Election?

We combine the Chinese retaliatory tariff shock and US agricultural subsidies in one unified framework to analyze the integrated effect on the 2020 presidential election. What was the combined impact of Chinese agricultural trade policy and US agricultural policy on the 2020 presidential election? To do so, we estimate the following first-difference (FD) regression model:

$$\Delta RV_c^{2020-2016} = \beta NetMFP_c + \gamma \Delta RV_c^{2016-2012} + \delta RV_c^{2016} + \theta X_c + \psi_s + \varepsilon_c \tag{6}$$

where c denotes county. $\Delta \mathrm{RV}_c^{2020-2016}$ refers to the change in the Republican vote share between the 2016 and 2020 presidential elections. Net $\mathrm{MFP}_c = \left(\mathrm{MFP}_c - \kappa \times \mathrm{Chn\_Ag\_TS}_c\right)$ means "Net MFP", which is defined by calculating the difference between an MFP payment and an adjusted Chinese agricultural retaliatory tariff.[44] Note that when T = 2, the

[44]See Section 4.2 for more details.

first-difference (FD) estimator and fixed effects estimator are equivalent. Hence, the FD estimator can avoid bias by controlling for some unobserved and time-invariant county characteristics.

$\Delta \mathrm{RV}_c^{2016-2012}$ is the change in the Republican vote share between the 2012 and 2016 presidential elections, which controls for a pre-existing trend in the change in the Republican vote share. RV_c^{2016} refers to the Republican vote share in the 2016 presidential election. In Section 4, Chinese tariff retaliation, the US agricultural subsidy, and Republican support in 2016 are all positively correlated. Hence, RV_c^{2016} in equation (6) controls for county-level support for the Republican Party in 2016, so our main coefficient of interest, β, can be interpreted as the impact of both trade policies on the change in the Republican vote share between the 2016 and 2020 US presidential elections after purging existing voting patterns and pre-existing trends at the county level.

Even after accounting for endogeneity by controlling for time-invariant county characteristics through first-differencing, pre-existing trends, and existing voting patterns, there remain some concerns about claiming causality in our approach (e.g., reverse causality and omitted variable bias). Reverse causality is not an issue, however, since the 2020 election outcomes could not have influenced China's retaliatory tariff shock and the corresponding US agricultural subsidies (see Section 2 for more details). The remaining concern about establishing causality would be the issue of potentially confounding omitted variables. We therefore add potentially confounding variables to alleviate concerns about endogeneity.

To control for potentially confounding factors that might simultaneously have affected the US and Chinese agricultural policies and the change in the Republican vote share between 2016 and 2020, we include a set of county-level control variables, X_c.[45] The COVID-19 pandemic was a key factor in the 2020 presidential election (Baccini, Brodeur, and Weymouth, 2021). We include COVID-19 cumulative deaths (and cases) per 1,000 population

[45] Appendix Tables A.2 and A.3 present the summary statistics for these county controls.

as of November 2, 2020, just one day before Election Day, in equation (6). Furthermore, one could argue that the effect of COVID-19 was even broader than the incidence of cases and deaths. For instance, COVID-19 had economic and social impacts related to the imposition of stay-at-home orders and mask mandates that may have affected counties differentially within a state.[46] To alleviate the concern, we include two additional variables that attempt to measure the incidence of COVID-19 mitigation strategies at the county level: (1) the number of days from April 10, 2020, to November 2, 2020, that a county imposed mask mandates; (2) the number of days that a county imposed stay-at-home orders between March 15, 2020, and May 5, 2020.[47]

Another pattern in the 2020 presidential election was the shift of minority and women voters toward Trump relative to the 2016 presidential election. We include population share and its change by gender and four races (White, Black, Asian, and Hispanic) in equation (6) to control for this shift. Many commentators expressed a belief that the relief checks issued by the Treasury at the start of COVID increased support for Trump. The distribution of household annual income and its change by eight-income bins can control for the stimulus checks because eligibility requirements were commonly based on income. Health care policy was also an important issue. Trump was a fierce adversary of the Affordable Care Act (ACA) while Biden wanted to enhance the ACA. We include the health insurance coverage rate and its change in equation (6). We also include the number of demonstrations associated with the BLM movement during the period of May 25, 2020 (the day of the death of George Floyd) to November 2, 2020 (one day before the presidential election) to control for the Black Lives Matter movement.[48] X_c also includes

[46]Based on the CDC datasets above, stay-at-home orders and mask mandates were imposed mostly at the state level. Hence, the state fixed effects in equation (6) can alleviate this concern to a certain extent. Nevertheless, there were a few exceptional cases of within-state variations between counties, although they were quantitatively small.

[47]The original data are sourced from the CDC in which county-level stay-at-home orders and mask mandates are recorded by day.

[48]The dataset comes from the Armed Conflict Location & Event Data Project (ACLED), which collects the dates, actors, locations, fatalities, and types of all reported political violence and protest events around the world. For more information, refer to the following website: www.acleddata.com. During the period above, ACLED records 9,552 demonstrations linked to the BLM movement in all 50 states and Washington,

the (log) median and mean household annual incomes, labor force participation rate, unemployment rate, population share by four education levels, seven age bins, and share of the voting age population.

Lastly, ψ_s are state fixed effects, which can control for state-specific trends.[49] Hence, the identification of our key coefficient is based on within-state and between-county variations. We weight counties by each county's total voting-age population in the year 2016. We cluster standard errors at the state level to allow for errors to be correlated within states.

Table 6 shows the estimation results. Across all columns in Table 6, the impacts of Net MFP on the Republican vote share are all positive and statistically significant at the 10 percent level. This result implies that the US agricultural subsidy, which was intended to mitigate the Chinese retaliatory tariff, overcompensated some US voters and led to an increase in Republican vote share. Quantitatively, a one standard deviation ($938) increase in exposure to Net MFP is associated with about a 0.38 percentage point (0.0004 $\times$ $938) increase in the Republican vote share.

China's retaliatory tariffs led ultimately to increased support for the Republican Party.[50] China's retaliation tariffs disproportionately targeted the agricultural sector and American farmers, a politically influential interest group. Those retaliation tariffs appeared intended to ease the trade restrictions that the US had imposed against China.[51] How-

DC. We aggregated the original dataset (at the event level) up to the county level. In each county, we count the number of demonstrations associated with the BLM movement during the period to capture the tensions associated with the death of George Floyd, resulting in protests, riots, and backlash against BLM.

[49] Note that the state fixed effects in the first-difference (FD) model in equation (6) is equivalent to the state by time fixed effects in the fixed effects estimation model.

[50] The universe of actual county-level MFP disbursement data allows us to assess the net election effect of Chinese agricultural trade policy and US agricultural policy in one unified framework.

[51] China's retaliatory tariffs during the US-China trade war were not the only example of politically motivated tariffs. In 2003, in response to the US steel tariff, the European Union threatened to impose tariffs on products ranging from Florida oranges to cars produced in Michigan in order to hurt the president in key marginal states. The threat of retaliation tariffs led President George W. Bush to reconsider the US tariffs on steel, which prevented a tariff war between the US and the EU. We conjecture that China's intention in imposing retaliatory tariffs was to cause the US to lift the trade restrictions it had imposed on China. However, unlike the 2003 US steel tariff case, the chain of tariff impositions between the US and China and subsequent US agricultural subsidies led unexpectedly to a trade war that generated a deadweight loss in exchange for political support.

Table 6: Republican Vote Share and Net MFP

Dependent Variable:	Δ Rep. Vote Share (2020 - 2016)				
	(1)	(2)	(3)	(4)	(5)
Net MFP	0.0006*	0.0013***	0.0012***	0.0005**	0.0004**
	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Δ Rep. Vote Share (2016 - 2012)			0.3569***	0.1966***	0.1733***
			(0.0487)	(0.0440)	(0.0415)
Rep. Vote Share (2016)			-0.1233***	-0.0831***	-0.0773***
			(0.0158)	(0.0141)	(0.0101)
State FEs	No	Yes	Yes	Yes	Yes
County Controls in Levels	No	No	No	Yes	Yes
County Controls in Changes	No	No	No	No	Yes
Observations	3,112	3,111	3,111	3,111	3,111
R-squared	0.0030	0.2375	0.5129	0.8170	0.8458

Note: The dependent variable is the change in the Republican share of the two party vote between the 2016 and 2020 US presidential elections. Washington, D.C., has no counties. Hence, when we add state-fixed effects, we lose one observation from Column (2). Observations are weighted by each county's total voting-age population in the year 2016. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

ever, President Trump ratcheted the tensions up even further by subsidizing US farmers through the MFP, a move that may have further increased the Republican vote share.

5.2 Robustness

Even after accounting for many confounding factors, perhaps the most immediate remaining threat to the interpretation of the observed increase in the Republican vote share in response to the Net MFP is that the Coronavirus Food Assistance Program (CFAP) payments may be compounded in the US agricultural subsidies. The Coronavirus Food Assistance Program (CFAP) is another ad hoc farm subsidy to assist the US agricultural producers impacted by both domestic and international market disruptions due to the COVID-19 outbreak.[52] Recent studies on this topic have suggested that the CFAP pay-

[52]USDA announced two rounds of CFAP in May and September 2020 up to $16 billion and $14 billion in payments, respectively, and paid out $10.6 and $13.1 billion, respectively, in direct payment assistance to producers. CFAP direct payments are intended to partially offset the loss of market revenue from the price decline, and the unexpected carry-cost of unsold commodities for producers and ranchers of products that have been negatively affected by COVID-19 (Schnepf and Monke, 2020).

ments can be considered broadly to be trade aid payments (Orden 2020; Zhang 2021; Glauber 2021; Janzen et al. 2021; Rawlings 2021). We thus consider CFAP payments to be a component of US agricultural policy, add CFAP payments to the Net MFP, and re-estimate equation (6).[53] Table 7 shows the estimation results. Reassuringly, across all columns, our key coefficients are all positive and statistically significant at the 10 percent level.[54]

Table 7: Republican Vote Share, Net MFP, and CFAP

Dependent Variable:	Δ Rep. Vote Share (2020 - 2016)				
	(1)	(2)	(3)	(4)	(5)
Net MFP + CFAP	0.0003*	0.0007***	0.0007***	0.0004***	0.0003**
	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Δ Rep. Vote Share (2016 - 2012)			0.3537***	0.1955***	0.1731***
			(0.0484)	(0.0438)	(0.0413)
Rep. Vote Share (2016)			-0.1243***	-0.0832***	-0.0775***
			(0.0158)	(0.0140)	(0.0100)
State FEs	No	Yes	Yes	Yes	Yes
County Controls in Levels	No	No	No	Yes	Yes
County Controls in Changes	No	No	No	No	Yes
Observations	3,112	3,111	3,111	3,111	3,111
R-squared	0.0027	0.2387	0.5162	0.8177	0.8462

Note: The dependent variable is the change in the Republican share of the two party vote between the 2016 and 2020 US presidential elections. Washington, D.C., has no counties. Hence, when we add state-fixed effects, we lose one observation from Column (2). Observations are weighted by each county's total voting-age population in the year 2016. Standard errors are clustered at the state level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

[53] We got access to the CFAP payments from the following website: https://www.fsa.usda.gov/news-room/efoia/electronic-reading-room/frequently-requested-information/payment-files-information/index. We then aggregated the CFAP payments up to the county level.

[54] In a similar vein, Janzen et al. (2021) also find that the ad hoc subsidies of MFP and CFAP programs increased Republican voting share in the 2020 Presidential Election at the county level. Unlike our analyses, however, they did not consider the tariff shock. Despite the difference, both their analysis and ours, taken together, suggest that the trade war influenced county-level voting outcomes.

6 Tariffs, Subsidies, and the Polarization of US Politics

So far, we have found evidence that China's agricultural retaliatory tariff and the corresponding US agricultural subsidy led to an increase in the Republican vote share in the 2020 presidential election. In Appendix B, we investigated whether the two policies affected the counterfactual aggregate election outcome – i.e., how many more Electoral College votes Republicans would have won in the absence of the two policies. We found that the two policies likely had no impact on the number of states that Republicans carried.[55] Then, using the counterfactual analysis results, in Section 6.1 we look at how the two policies contributed to partisan polarization, and in Section 6.2 at how they contributed to the rural-urban political polarization.

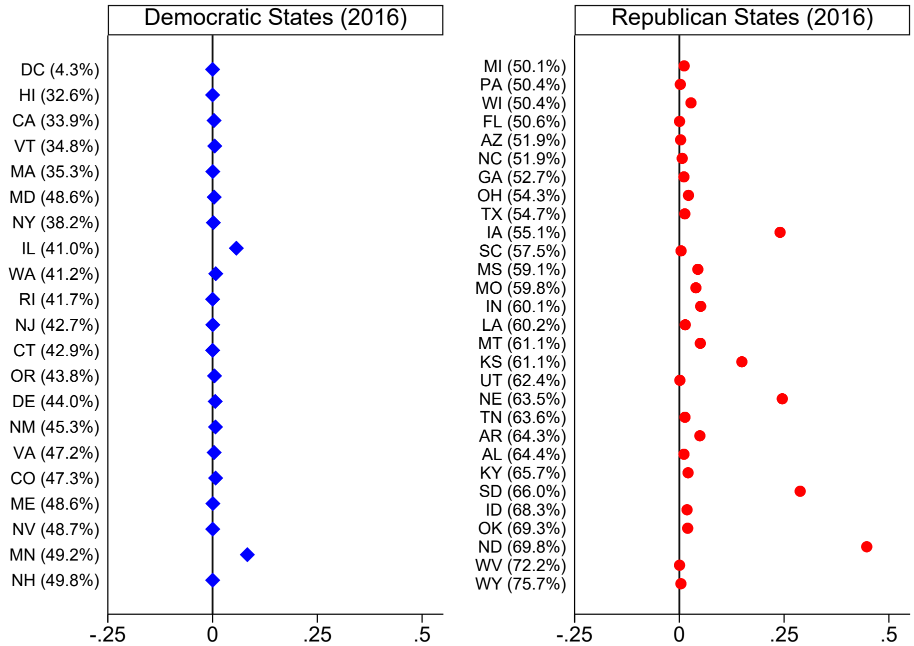
6.1 Partisan Polarization

Although our counterfactual analysis shows that China's retaliatory agricultural tariff and the corresponding US agricultural subsidy likely had no impact on the number of Electoral College votes, we find evidence that the two policies did exacerbate partisan polarization.[56] Figure 7 shows the implied effect of the Net MFP on the Republican vote share in 2020 at the state level. The implied effects were especially high in Republican states where the Republican vote share was higher than 55% in 2016. The average of the implied effect of the Net MFP (across states) in solidly Republican states is 0.077 percentage point, with a range between 0.000 and 0.447. On the other hand, the implied effects were almost negligible in those solidly Democratic states where the Democratic vote share was higher than 55% in 2016. The average of the implied effect of the Net MFP in solidly Democratic states is 0.007 percentage point, with a range between 0.000 and 0.057.

[55] See Appendix Table B.1 for more details.

[56] Political polarization is defined as the divergence of political attitudes towards ideological/political extremes (Baldassarri and Gelman, 2008; Fiorina, Abrams et al., 2008). While there exist diverse ways to gauge political polarization, we measure an aspect of political polarization using voting behaviors. Specifically, we define partisan polarization in this section such that US states that have more polarized voting outcomes before the trade war show larger implied effects of the Net MFP on voting outcomes.

Figure 7: The Implied Effect of the Net MFP on Political Polarization in the 2020 Election

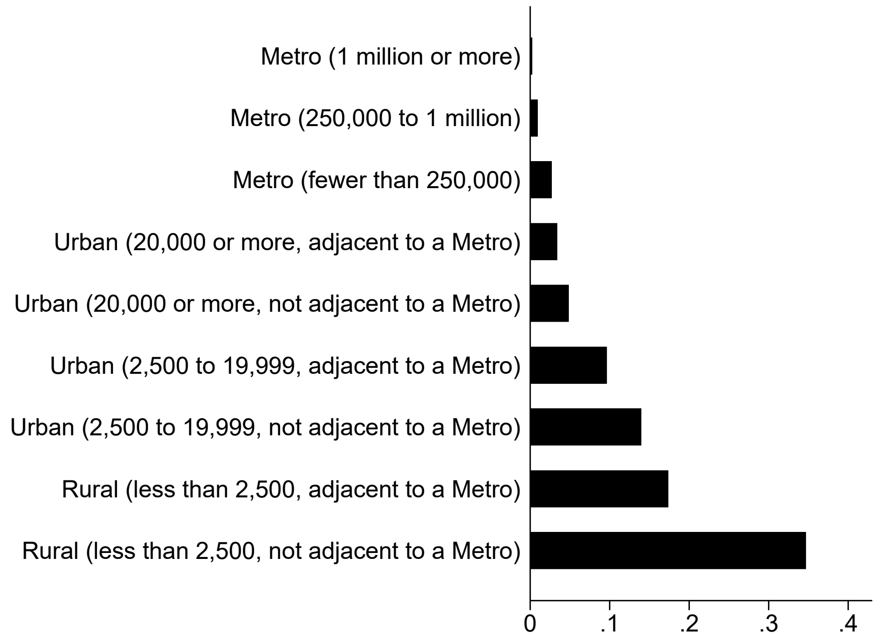


Note: "Republican (or Democratic) States (2016)" refers to states where the Republican share of the two-party vote is greater than 0.5 (less than 0.5) in the 2016 presidential election. The number in parentheses is the Republican vote share (%) in the 2016 presidential election for each state. Alaska is excluded. Two congressional districts, NE-02 and ME-02, are absorbed into NE and ME, respectively. States are ordered according to the Republican vote share (%) in the 2016 presidential election in each panel. The unit of measure on the horizontal axis is percent. Each dot represents the implied change in the Net MFP on the Republican vote share in 2020. The estimates are calculated using the point estimates from the full specification in Column (5) of Table 6. We aggregate the county-level points up to the state level.

This finding can shed some light on the recent literature that finds links between economic shocks and sustained increases in partisan polarization (e.g., Mian, Sufi, and Trebbi 2014; Autor, Dorn, Hanson, and Majlesi 2020; Baker, Baksy, Bloom, Davis, and Rodden 2020; Coibion, Gorodnichenko, and Weber 2020). In particular, our finding is close to that of Autor et al. (2020), who unraveled how rising import competition contributed to the polarization of US politics. However, to our knowledge, there are still few empirical studies on the issue. We provide empirical evidence that US agricultural policy in response to the Chinese retaliatory trade policy heightened the partisan divide.

6.2 Rural-Urban Political Polarization

Figure 8: The Implied Effect of the Net MFP on Rural-Urban Polarization in the 2020 Election



Note: Metro-Urban-Rural counties are defined by the 2013 USDA-ERS Rural-Urban continuum codes. Metropolitan (Metro) counties are defined by the population size of their metro area and non-metropolitan (Urban and Rural) counties are defined by the degree of urbanization and adjacency to metro areas. Metro counties are categorized into three groups by the total population size of the metro area and non-metro counties are categorized into six groups based on the total urban population and distance to a metro area. The phrases in parentheses describe each category. The estimates are calculated using the point estimates from the full specification in Column (5) of Table 6. We aggregate the county-level points for each rural-urban category. The unit of the horizontal axis (the implied effect of the Net MFP) is percent. Alaska is excluded.

We find further evidence that the unexpected outbreak of the US-China trade war exacerbated rural-urban political polarization. Figure 8 presents the implied effect of the Net MFP on the Republican vote share in 2020 at the metro, urban, and rural levels.[57] We find that the implied effect of the Net MFP increases monotonically from the most urban area to the most rural area. In the three metro areas, the implied effects of the Republican

[57] We distinguish between metro, urban, rural counties and divide those counties into nine regional categories following the 2013 USDA-ERS rural-urban continuum codes. Similar to the state-level analysis in Figure 7, we aggregate counterfactual county-level Republican votes cast for each metro, urban, and rural category.

vote shares are relatively small, ranging from 0.002% to 0.027%. In the four urban areas, the implied effects of the two-party Republican vote shares are slightly larger than in the metro areas, ranging 0.034% to 0.140%. In the two rural areas, the implied effects of the Republican vote shares are larger than in the other areas, ranging from 0.174% to 0.347%. The results suggest that although the rural-urban divide was not caused by the US-China trade war, the two countries' trade policies heightened it.[58]

7 Conclusion

Retaliatory tariffs by China during the US-China trade war covered major US agricultural products, adversely affecting US farmers. Immediately after the retaliation, the Trump administration began providing assistance to US farmers through the Market Facilitation Program (MFP), which was intended to mitigate farmers' losses related to the trade war. Those two policies seem to have offset each other in affecting US farmers' support for the Republican Party. The effect of the trade war, specifically Chinese agricultural tariffs, and the US agricultural subsidy, on the 2020 presidential election is unclear. Although there are approximately 2 million farms in operation in the United States, farmers can be crucial in many swing states, such as those in the Midwest where the margin of victory is expected to be slim. Therefore, assessing the net election effect of those two agricultural policies is crucial for our understanding of the 2020 presidential election and more broadly for our understanding of how economic shocks, especially trade policies, shape the US political landscape.

It has been argued that the two countries' trade policies may have affected the 2020 presidential election, but to the best of our knowledge few studies have investigated the net election effect. This is partly because measuring county-level agricultural tariff exposure is challenging, and MFP payment data have been unavailable to researchers at the

[58] Refer to the following studies on the issue of rural-urban political polarization in the US: Fiorina, Abrams et al. 2008; McKee 2008; Scala and Johnson 2017.

county level. Using actual county-level disbursement of US MFP payments, along with county-level Chinese agricultural retaliatory tariff exposure that we refined in the context of the US agricultural sector, we overcome the data limitation and provide empirical evidence on how trade policies can affect political outcomes.

Our core findings are as follows. The Net MFP was distributed disproportionately to the Republican base, implying that the Trump administration allocated rents in exchange for political patronage. We find that US agricultural subsidies overcompensated some US voters, leading to an increase in the Republican vote share in the 2020 presidential election. We further find that US and Chinese agricultural trade policies unexpectedly contributed to rising political polarization, especially the rural-urban divide. Collectively, our findings thus contribute one additional piece of empirical evidence to the literature on the political economy of trade protection (e.g., Mayer 1984; Grossman and Helpman 1994, 1995).

References

Adjemian, M.K., A. Smith, and W. He. 2021. "Estimating the market effect of a trade war: The case of soybean tariffs." *Food Policy* 105:102152.

Alesina, A., N. Roubini, and G.D. Cohen. 1997. *Political cycles and the macroeconomy*. MIT press.

Anderson, K., G. Rausser, and J. Swinnen. 2013. "Political economy of public policies: insights from distortions to agricultural and food markets." *Journal of Economic Literature* 51:423–77.

Autor, D., D. Dorn, G. Hanson, and K. Majlesi. 2020. "Importing political polarization? The electoral consequences of rising trade exposure." *American Economic Review* 110:3139–83.

Baccini, L., A. Brodeur, and S. Weymouth. 2021. "The COVID-19 pandemic and the 2020 US presidential election." *Journal of Population Economics* 34:739–767.

Baker, S.R., A. Baksy, N. Bloom, S.J. Davis, and J.A. Rodden. 2020. "Elections, political polarization, and economic uncertainty." NBER Working Paper No. 27961.

Baldassarri, D., and A. Gelman. 2008. "Partisans without constraint: Political polarization and trends in American public opinion." *American Journal of Sociology* 114:408–446.

Balistreri, E.J., W. Zhang, and J. Beghin. 2020. "The State-level Burden of the Trade War: Interactions between the Market Facilitation Program and Tariffs." *Agricultural Policy Review* 2020:1.

Banful, A.B. 2011. "Old problems in the new solutions? Politically motivated allocation of program benefits and the "new" fertilizer subsidies." *World Development* 39:1166–1176.

Bellemare, M.F., and N. Carnes. 2015. "Why do members of congress support agricultural protection?" *Food Policy* 50:20–34.

Blanchard, E.J., C.P. Bown, and D. Chor. 2019. "Did Trump's Trade War Impact the 2018 Election?" NBER Working Paper No. 26434.

Bombardini, M., B. Li, and F. Trebbi. 2020. "Did US Politicians Expect the China Shock?" NBER Working Paper No. 28073.

Bown, C.P. 2020. "Trump's Trade War Timeline: An Up-to-Date Guide." Working paper.

Brutger, R., S. Chaudoin, and M. Kagan. 2021. "Trade War or Election Interference?" Working paper.

Canen, N., C. Kendall, and F. Trebbi. 2020. "Unbundling polarization." *Econometrica* 88:1197–1233.

Carter, C., J. Dong, and S. Steinbach. 2020. "2018 Trade War, Mitigation Payments, and California Agriculture." *Agricultural and Resource Economics ARE update* 24.

Carter, C.A., and S. Steinbach. 2020. "The impact of retaliatory tariffs on agricultural and food trade." NBER Working Paper No. 27147.

Cavallo, A., G. Gopinath, B. Neiman, and J. Tang. 2021. "Tariff pass-through at the border and at the store: Evidence from us trade policy." *American Economic Review: Insights* 3:19–34.

Chang, H.H., and D. Zilberman. 2014. "On the political economy of allocation of agricultural disaster relief payments: application to Taiwan." *European Review of Agricultural Economics* 41:657–680.

Che, Y., Y. Lu, J.R. Pierce, P.K. Schott, and Z. Tao. 2016. "Does Trade Liberalization with China Influence U.S. Elections?" NBER Working Paper No. 22178.

Coibion, O., Y. Gorodnichenko, and M. Weber. 2020. "Political polarization and expected economic outcomes." NBER Working Paper No. 28044.

Collins, K. 1989. "The Political Economy of US Agricultural Policy: Discussion." *American Journal of Agricultural Economics* 71:1175–1176.

Cox, G.W., and M.D. McCubbins. 1986. "Electoral politics as a redistributive game." *Journal of Politics* 48:370–389.

De Gorter, H., and J. Swinnen. 2002. "Political economy of agricultural policy." *Handbook of agricultural economics* 2:1893–1943.

DellaVigna, S., and E. Kaplan. 2007. "The Fox News effect: Media bias and voting." *Quarterly Journal of Economics* 122:1187–1234.

Dutt, P., and D. Mitra. 2005. "Political ideology and endogenous trade policy: an empirical investigation." *Review of Economics and Statistics* 87:59–72.

Fajgelbaum, P., and A. Khandelwal. 2021. "The economic impacts of the US-China trade war." NBER Working Paper No. 29315.

Fajgelbaum, P.D., P.K. Goldberg, P.J. Kennedy, and A.K. Khandelwal. 2020. "The return to protectionism." *Quarterly Journal of Economics* 135:1–55.

Fetzer, T., and C. Schwarz. 2021. "Tariffs and politics: Evidence from trump's trade wars." *Economic Journal* 131:1717–1741.

Fiorina, M.P., S.J. Abrams, et al. 2008. "Political polarization in the American public." *Annaul Review of Political Science* 11:563.

Fisher, D.U., and R.D. Knutson. 2013. "Uniqueness of agricultural labor markets." *American Journal of Agricultural Economics* 95:463–469.

GAO. 2020. "USDA Market Facilitation Program: Information on Payments for 2019." Working paper.

Garrett, T.A., T.L. Marsh, and M.I. Marshall. 2006. "Political allocation of US agriculture disaster payments in the 1990s." *International Review of Law and Economics* 26:143–161.

Garrett, T.A., and R.S. Sobel. 2003. "The political economy of FEMA disaster payments." *Economic inquiry* 41:496–509.

Gelman, A., B. Shor, J. Bafumi, and D. Park. 2005. "Rich state, poor state, red state, blue state: What's the matter with Connecticut?" Working paper.

Glauber, J.W. 2021. "US trade aid payments and the WTO." *Applied Economic Perspectives and Policy* 43:586–603.

Goldberg, P.K., and G. Maggi. 1999. "Protection for sale: An empirical investigation." *American Economic Review* 89:1135–1155.

Grossman, G.M., and E. Helpman. 1994. "Protection for Sale." *American Economic Review*, pp. 833–850.

—. 1995. "Trade wars and trade talks." *Journal of Political Economy* 103:675–708.

Janzen, J.P., and N.P. Hendricks. 2020. "Are Farmers Made Whole by Trade Aid?" *Applied Economic Perspectives and Policy* 42.

Janzen, J.P., T. Malone, K.A. Schaefer, and D.P. Scheitrum. 2021. "Political returns to ad hoc farm payments?" Applied economic perspectives and policy (forthcoming).

Jensen, J.B., D.P. Quinn, and S. Weymouth. 2016. "Winners and losers in international trade: The effects on US presidential voting." NBER Working Paper No. 21899.

Kim, S.E., and Y. Margalit. 2021. "Tariffs As Electoral Weapons: The Political Geography of the US–China Trade War." *International organization* 75:1–38.

Klomp, J., and J. De Haan. 2013. "Conditional election and partisan cycles in government support to the agricultural sector: An empirical analysis." *American Journal of Agricultural Economics* 95:793–818.

Lake, J., and J. Nie. 2022. "The 2020 US Presidential Election and Trump's Trade War." CESifo Working Paper No. 9669.

Li, M., W. Zhang, and C. Hart. 2018. "What have we learned from China's past trade retaliation strategies?" *Choices* 33:1–8.

Lindbeck, A., and J.W. Weibull. 1987. "Balanced-budget redistribution as the outcome of political competition." *Public Choice* 52:273–297.

Liu, X., and B.E. Kirwan. 2020. "Political influence in the distribution of agricultural disaster payments." *Applied Economics* 52:5613–5628.

Mason, N.M., T.S. Jayne, and N. Van De Walle. 2017. "The political economy of fertilizer subsidy programs in Africa: Evidence from Zambia." *American Journal of Agricultural Economics* 99:705–731.

Mayda, A.M., G. Peri, and W. Steingress. 2022. "The political impact of immigration: Evidence from the United States." *American Economic Journal: Applied Economics* 14:358–89.

Mayer, W. 1984. "Endogenous tariff formation." *American Economic Review* 74:970–985.

McKee, S.C. 2008. "Rural voters and the polarization of American presidential elections." *PS: Political Science and Politics* 41:101–108.

Mian, A., A. Sufi, and F. Trebbi. 2014. "Resolving debt overhang: Political constraints in the aftermath of financial crises." *American Economic Journal: Macroeconomics* 6:1–28.

Nordhaus, W.D. 1975. "The political business cycle." *Review of Economic Studies* 42:169–190.

Orden, D. 2020. "Resilience and Vulnerabilities of the North American Food System during the Covid-19 Pandemic." *EuroChoices* 19:13–19.

Park, H.J., and N. Jensen. 2007. "Electoral competition and agricultural support in OECD countries." *American Journal of Political Science* 51:314–329.

Persson, T., and G.E. Tabellini. 2002. *Political economics: explaining economic policy*. MIT press.

Rawlings, T. 2021. "The Impacts of the United States-China Trade War on the Texas Cotton Sector." Working paper.

Ridley, W., and S. Devadoss. 2022. "Determinants of Policy Responses in the US-China Tit-for-Tat Trade War." Working paper.

Rogoff, K. 1990. "Equilibrium Political Budget Cycles." *American Economic Review* 80:21–36.

Rogoff, K., and A. Sibert. 1988. "Elections and Macroeconomic Policy Cycles." *Review of Economic Studies* 55:1–16.

Russell, L.A. 2018. "Ideology, Electoral Incentives, PAC Contributions, and the Agricultural Act of 2014." *Journal of Agricultural and Resource Economics*, pp. 274–291.

Scala, D.J., and K.M. Johnson. 2017. "Political polarization along the rural-urban continuum? The geography of the presidential vote, 2000–2016." *The ANNALS of the American Academy of Political and Social Science* 672:162–184.

Schnepf, R.D., and J. Monke. 2020. *COVID-19, US Agriculture, and USDA's Coronavirus Food Assistance Program (CFAP)*. Congressional Research Service.

Schnitkey, G., N. Paulson, K. Swanson, and J. Coppess. 2019. "The 2019 Market Facilitation Program." *FarmdocDaily* 9.

USDA. 2019. "Trade Damage Estimation for the 2019 Market Facilitation Program and Food Purchase and Distribution Program." Working paper.

—. 2018. "Trade Damage Estimation for the Market Facilitation Program and Food Purchase and Distribution Program." Working paper.

Zhang, W. 2021. "The Case for Healthy US-China Agricultural Trade Relations despite Deglobalization Pressures." *Applied Economic Perspectives and Policy* 43:225–247.

Appendix

Appendix A: Additional Tables

Table A.1: U.S. Agricultural Exports to China, 2015-2020

Commodity (Values in $ billions)	NAICS	2015	2016	2017	2018	2019	2020
Crop Production	111	14.86	17.25	15.78	5.85	10.28	20.65
Oilseeds & Grain Farming	1111	12.98	15.52	13.60	3.81	8.32	17.19
Soybean Farming	11111	10.49	14.20	12.22	3.12	8.00	14.20
Wheat Farming	11114	0.16	0.21	0.35	0.11	0.55	0.57
Corn Farming	11115	1.62	0.39	1.42	0.50	0.57	1.21
Vegetables & Melon Farming	1112	0.03	0.03	0.05	0.04	0.04	0.03
Fruits & Tree Nut Farming	1113	0.31	0.34	0.45	0.43	0.71	0.82
Mushrooms, Nursery, Floriculture	1114	0.15	0.11	0.16	0.20	0.21	0.15
Other Crop Farming	1119	1.53	1.35	1.67	1.55	1.19	2.60
Animal Production & Aquaculture	112	0.19	0.14	0.11	0.05	0.05	0.08
Agricultural Products	111 & 112	15.05	17.39	15.89	5.90	10.33	20.73

Source: US Census Bureau trade statistics.
Notes: NAICS codes that fall under 11 (Agriculture, Forestry, Fishing and Hunting) include Crop production (111), Animal production & aquaculture (112), Forestry & logging (113), Fishing, Hunting, & Trapping (114), and Support Activities for Agriculture and Forestry (115). We define agricultural products as those classified in NAICS 111 and NAICS 112, which are fundamentally related to Market Facilitation Program payments.

Table A.2: Summary Statistics (County Controls, 2016)

Variables	Mean	SD	Min	Max	Format
Panel A. Industry Characteristics					
Employment share in agriculture and mining	6.89	7.45	0.00	59.30	Percent
Employment share in manufacturing	12.31	7.11	0.00	48.30	Percent
Panel B. Economic Characteristics					
HH annual income, below $25k share	26.78	8.19	5.50	60.00	Percent
HH annual income, $25k-35k share	11.50	2.40	2.90	24.00	Percent
HH annual income, $35k-50k share	14.70	2.43	2.70	33.70	Percent
HH annual income, $50k-75k share	18.54	2.79	6.60	30.20	Percent
HH annual income, $75k-100k share	11.67	2.71	1.30	32.40	Percent
HH annual income, $100k-150k share	10.72	3.96	1.30	27.80	Percent
HH annual income, $150k-200k share	3.26	2.16	0.00	16.30	Percent
HH annual income, over $200k share	2.84	2.56	0.00	25.30	Percent
Log Median HH annual income	10.74	0.25	9.85	11.74	Log
Log Mean HH annual income	11.02	0.22	10.30	12.01	Log
Labor force participation rate	58.71	7.90	14.50	80.40	Percent
Unemployment rate	7.07	3.25	0.00	29.93	Percent
Panel C. Demographic Characteristics					
Less than high school share	14.23	6.54	1.28	51.48	Percent
High school graduate share	34.58	7.07	6.46	54.64	Percent
Some college share	21.88	3.79	8.29	36.33	Percent
College graduates or more share	29.31	9.73	8.22	83.20	Percent
Population share, Female	49.98	2.33	21.50	58.50	Percent
Population share, White	83.70	16.35	4.60	100.00	Percent
Population share, Black	9.09	14.56	0.00	86.20	Percent
Population share, Asian	1.25	2.53	0.00	42.90	Percent
Population share, Hispanic	8.99	13.65	0.00	99.00	Percent
Population share, Age under 15	18.62	3.01	1.50	34.80	Percent
Population share, Age 15-24	12.95	3.51	3.00	58.40	Percent
Population share, Age 25-34	11.63	2.24	0.00	26.80	Percent
Population share, Age 35-44	11.66	1.58	3.30	20.80	Percent
Population share, Age 45-54	13.54	1.50	2.60	24.80	Percent
Population share, Age 55-64	13.96	2.25	3.20	44.80	Percent
Population share, Age over 65	17.63	4.45	3.90	53.10	Percent
Voting age population share	74.87	5.32	43.13	95.09	Percent
Health insurance coverage rate	87.83	5.11	53.40	97.90	Percent
Panel D. COVID-19					
Cumulative deaths as of Nov 2, 2020	0.58	0.61	0.00	6.41	Count per 1k pop
Cumulative cases as of Nov 2, 2020	29.32	17.80	0.00	178.72	Count per 1k pop
Stay-at-home orders (from March 15 to May 5, 2020)	35.70	12.70	0.00	51.00	# of days
Mask mandates (from April 10, 2020 to Nov 2, 2020)	89.92	67.76	0.00	207.00	# of days
Panel E. Black Lives Matter Movement					
Demonstrations (from May 25, 2020 to Nov 2, 2020)	3.06	11.02	0.00	218.00	# of cases

Sources: The variables in Panels A., B., and C. are from the US Census ACS data in 2016. The COVID-19 variables in Panel D. come from the CDC and Covid Act Now (CAN). In Panel E., the data are from ACLED.
Note: N = 3,112 counties. In Panel B, HH annual income represents the income of the householder and all other individuals 15 years old and over in the household. Labor force participation rate represents the proportion of the total population aged 16 and over that is in the labor force. In Panel C, the voting-age population is defined by the Bureau of the Census as all U.S. citizens residing in the United States, aged 18 and older. Health insurance coverage rate includes both public and private health insurance.

Table A.3: Summary Statistics (County Controls, Changes between 2012 and 2016)

Variables	Mean	SD	Min	Max	Format
Panel A. Industry Characteristics					
Δ Employment share in agriculture and mining	-0.02	2.15	-19.70	25.60	Δ Percent
Δ Employment share in manufacturing	0.09	2.15	-12.50	16.10	Δ Percent
Panel B. Economic Characteristics					
Δ HH annual income, below $25k share	-1.38	3.11	-23.00	20.00	Δ Percent
Δ HH annual income, $25k-35k share	-0.46	2.01	-14.00	10.80	Δ Percent
Δ HH annual income, $35k-50k share	-0.44	2.34	-13.50	14.70	Δ Percent
Δ HH annual income, $50k-75k share	-0.24	2.47	-17.80	16.00	Δ Percent
Δ HH annual income, $75k-100k share	0.25	2.07	-15.40	23.80	Δ Percent
Δ HH annual income, $100k-150k share	1.13	1.90	-8.00	15.30	Δ Percent
Δ HH annual income, $150k-200k share	0.56	0.96	-7.80	6.20	Δ Percent
Δ HH annual income, over $200k share	0.59	1.00	-5.80	8.20	Δ Percent
Δ Log Median HH annual income	0.05	0.08	-0.64	0.64	Δ Percent
Δ Log Mean HH annual income	0.07	0.07	-0.32	0.55	Δ Percent
Δ Labor force participation rate	-1.64	2.75	-27.80	18.90	Δ Percent
Δ Unemployment rate	-1.55	2.30	-16.08	14.43	Δ Percent
Panel C. Demographic Characteristics					
Δ Less than high school share	-1.67	2.18	-14.39	15.57	Δ Percent
Δ High school graduate share	-0.42	2.76	-39.36	14.08	Δ Percent
Δ Some college share	0.01	2.26	-15.96	16.94	Δ Percent
Δ College graduate share	2.07	2.34	-14.69	11.55	Δ Percent
Δ Population share, Female	-0.06	1.17	-12.30	23.90	Δ Percent
Δ Population share, White	-0.52	2.82	-44.70	37.60	Δ Percent
Δ Population share, Black	0.04	0.99	-15.50	15.40	Δ Percent
Δ Population share, Asian	0.13	0.46	-3.90	7.20	Δ Percent
Δ Population share, Hispanic	0.65	1.29	-21.80	16.40	Δ Percent
Δ Population share, Age under 15	-0.49	1.18	-12.90	12.90	Δ Percent
Δ Population share, Age 15-24	-0.15	1.17	-7.50	8.70	Δ Percent
Δ Population share, Age 25-34	0.18	1.30	-34.10	17.50	Δ Percent
Δ Population share, Age 35-44	-0.60	0.94	-7.40	6.10	Δ Percent
Δ Population share, Age 45-54	-1.21	1.17	-19.80	9.50	Δ Percent
Δ Population share, Age 55-64	0.74	1.06	-12.00	22.40	Δ Percent
Δ Population share, Age over 65	1.54	1.26	-7.30	19.10	Δ Percent
Δ Health insurance coverage rate	2.88	2.54	-19.70	15.80	Δ Percent

Source: All variables are from the US Census American Community Survey data in 2012 and 2016 (5-Year estimates).
Note: Summary statistics across N = 3,112 counties.

Appendix B: Counterfactual Analysis

We compute the counterfactual county-level Republican vote shares under a scenario where the Chinese retaliatory tariff and US agricultural subsidy are removed. By subtracting $\widehat{\beta} \times \text{Net MFP}_c$ from the actual Republican vote share for county c in the 2020 presidential election, we obtain the counterfactual Republican vote share (or Republican votes cast) for each county where $\widehat{\beta}$ is from the full specification in Column (5) of Table 6. We then aggregate all counterfactual county-level Republican vote tallies up to the state level to measure the state-level counterfactual Republican votes cast. Appendix Table B.1 presents the counterfactual Republican vote share in the 2020 election. At the state level, we find that the two policies likely had no impact on the predicted number of states that Republicans carried. Under the counterfactual scenario, Republicans still carried 25 states, which is identical to the actual election outcome. Thus it appears that Chinese retaliation and US agricultural subsidies had little overall effect on the election outcome.

Table B.1: Counterfactual Republican Vote Share in the 2020 Election

Democratic States (2020)				Republican States (2020)			
State	Rep. Vote Share, %	Implied Effect, %	Counterfactual Rep. Vote Share, %	State	Rep. Vote Share, %	Implied Effect, %	Counterfactual Rep. Vote Share, %
DC	5.533	0.000	5.533	NC	50.684	0.007	50.677
VT	31.701	0.005	31.696	FL	51.695	0.000	51.694
MA	32.884	0.002	32.884	TX	52.831	0.013	52.818
MD	32.971	0.004	32.967	OH	54.077	0.022	54.055
HI	34.967	0.000	34.967	IA	54.183	0.240	53.943
CA	35.090	0.004	35.087	SC	55.927	0.004	55.923
NY	38.264	0.002	38.262	KS	57.493	0.149	57.344
RI	39.490	0.000	39.490	MO	57.836	0.039	57.796
CT	39.828	0.000	39.827	IN	58.195	0.051	58.144
WA	40.075	0.008	40.067	MS	58.380	0.044	58.335
DE	40.373	0.006	40.367	MT	58.397	0.050	58.347
IL	41.341	0.057	41.284	LA	59.464	0.014	59.450
OR	41.693	0.005	41.688	NE	59.784	0.246	59.538
NJ	41.929	0.000	41.928	UT	60.694	0.001	60.692
CO	43.062	0.007	43.054	TN	61.828	0.013	61.814
NM	44.482	0.007	44.475	AL	62.911	0.011	62.900
VA	44.845	0.004	44.842	KY	63.200	0.021	63.179
ME	45.535	0.001	45.535	SD	63.435	0.288	63.146
NH	46.252	0.000	46.251	AR	64.212	0.049	64.163
MN	46.361	0.083	46.278	ID	65.877	0.018	65.859
MI	48.586	0.011	48.575	OK	66.940	0.020	66.920
NV	48.777	0.000	48.777	ND	67.217	0.447	66.770
PA	49.399	0.002	49.397	WV	69.799	0.000	69.798
WI	49.681	0.028	49.653	WY	72.480	0.004	72.477
AZ	49.843	0.003	49.840				
GA	49.881	0.011	49.870				

Note: "Republican (or Democratic) States (2020)" refers to states where the Republican share of the two-party vote is greater than 0.5 (respectively, less than 0.5) in the 2020 presidential election. "Rep. Vote Share" refers to the Republican vote share (%) in the 2020 presidential election for each state. Alaska is excluded. Two congressional districts, NE-02 and ME-02, are absorbed into Nebraska and Maine, respectively. States are ordered according to the Republican vote share (%) in the 2020 presidential election in each panel. "Implied Effect" is the implied change in the Net MFP on the Republican vote share in 2020. The estimates are calculated based on the point estimates from the full specification in Column (5) of Table 6. We aggregate the county-level points for each state. "Counterfactual Vote Share" refers to the Republican vote share (%) in the absence of the Chinese agricultural retaliatory tariff and US agricultural subsidy.