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 first document that US agricultural subsidies relative to the Chinese retaliatory tariff exposure were especially higher in solidly Republican counties, implying that Trump allocated rents in exchange for political patronage. Then, we find that US agricultural subsidies outweighed 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 US agricultural policy exacerbated political polarization in the US, especially the rural-urban divide.

Keywords: Agricultural Subsidy; Trade War; Trade Policy; Presidential Election; Market Facilitation Program; Tariffs; Political Polarization; Political Budget Cycle
JEL Code: D72, F13, F14, Q17, Q18, I18

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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 widely practiced and oftentimes politically motivated such that tariffs and subsidies are granted in response to demands by special 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. The 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, Goldberg, Kennedy and Khandelwal, 2020). Those retaliation 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. Regarding the MFP1 and MFP2 payments, many raised concerns that they were not fairly distributed across counties and may have been determined by political considerations (Schnitkey, Paulson, Swanson and Coppess, 2019; Janzen and Hendricks, 2020; GAO, 2020; Balistreri, Zhang and Beghin, 2020; Carter, Dong and Steinbach, 2020).

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, Dorn, Hanson and Majlesi, 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 define 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, Republican-leaning counties were more directly targeted by Chinese retaliatory tariffs. Second, there was a positive association between the actual disbursements of 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).

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 Republican counties are more agriculturally oriented, 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 especially 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), implying that Trump allocated rents in exchange for political patronage.

We then analyze how Chinese agricultural trade policy and 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 two-party Republican vote share is positive. Quantitatively, a one standard deviation increase in exposure to Net MFP is associated with about a 0.44 percentage point increase in the Republican vote share. This result means that 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 retaliation tariffs, whose original purpose was to undermine Trump's political base in exchange for lifting trade restrictions that US had imposed on China.

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.

1.1 Related Literature

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, 2020; 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).[1] 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 find that the distribution of agricultural subsidies was allocated disproportionately to strong Republican 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 retaliation trade policy, can potentially be used as fiscal policy instruments during election periods. In a similar 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,

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

the "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, Dorn, Hanson and Majlesi (2020) find that rising import competition from China contributed to US polarization.[2] 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.[3] To the best of our knowledge, ours is the first to establish that trade policy can affect political polarization.

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 (e.g., Collins, 1989; De Gorter and Swinnen, 2002; Persson and Tabellini, 2002; Anderson, Rausser and Swinnen, 2013). Previous empirical studies have focused mostly on the politically motivated allocation of agricultural subsidies in the United States (Garrett and Sobel, 2003; 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 few empirical studies of how agriculture policy affects voting outcomes, especially in the US. By providing evidence on how agricultural policy affects political outcomes, we contribute to research at the nexus of political economics and agricultural economics.

Last, we make use of 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. These 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, 2020). Using the actual disbursement dataset, we were able to calculate the Net MFP – the difference between the MFP payment and

[2]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.

[3]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, 2021).

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.[4]

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 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 specifically focus 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.

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.[5] In April 2018, China 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 that 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

[4]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.

[5]Before the Section 232 tariffs, the first trade barrier 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 antidumping 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, the Section 201 retaliatory tariffs were not imposed.

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 refers 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."

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.

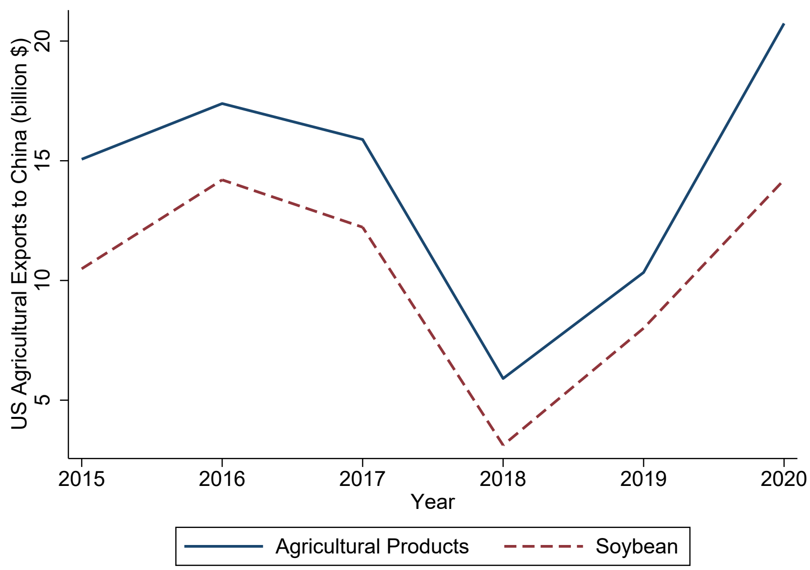
In September 2018, the US imposed a 10 percent tariff on $200 billion in products and China imposed a 5-10 percent tariff on $60 billion in products. In May 2019, the US raised the tariff rate on the Chinese product list from 10 percent to 25 percent. In June 2019, in response to the tariff hike, China 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.[6] Further, China agreed to reduce non-

[6]Note that the coverage of agricultural products in the Phase One agreement is broader than the one in our analysis. In our analysis, we define agricultural products as those classified in NAICS 111 and

tariff barriers that inhibited US exports of agriculture products.

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



Notes: Data come from US Census Bureau Trade. 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, and recorded $20.73 billion.[7]

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.[8] Hence, during the US-China trade

NAICS 112, which are fundamentally related to Market Facilitation Program payments. Hence, those listed amounts ($12.5 billion and $19.5 billion) would be smaller if confined to NAICS 111 and NAICS 112.

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

[8] In 2017, 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 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 already 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.[9] 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 up to $14.5 billion through MFP2 for 2019.[10] 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) is 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.[11] 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 exporting commodities to China, such as corn, soybeans, wheat, and cotton). County payment rates range from $15 to $150 per acre, depending on the exposure to trade retaliation in that county, which is determined by the USDA. For the MFP2, the payment rate base year is 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 includes "indirect export losses" in MFP2, which include economic costs associated with adjusting to the disrupted markets, managing surplus commodities, and developing new markets.

Regarding the structural change in MFP payment between 2018 and 2019 by the Trump administration, many raised concerns that the MFP distribution was being determined by

[9] 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.

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

[11] 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)

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

political considerations. GAO (2020) noted that big farms in strongly Republican South, disproportionately benefited from MFP. For example, Georgia farmers received more than twice the national average with the highest average per acre in the country.[12] In the same vein, 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 provide evidence that California farmers were under-compensated compared to Midwest and Southern

[12]Two articles in the Washington Post in 2019 and 2020 indicated that 9 out of every 10 counties that voted for Trump in 2016 received some support through the program; counties that voted for 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 statesâĂŤmeasured by average payments per acre of farmlandâĂŤwere in the South.

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 political economy of trade protection (Mayer, 1984; Grossman and Helpman, 1994, 1995) and their empirical findings (Goldberg and Maggi, 1999; Dutt and Mitra, 2005). Once we zoom in on politically-motivated agricultural subsidies, Klomp and De Haan (2013) found that public agricultural spending increases under the influence of 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 representation in Congress, although each state is entitled to at least three electors regardless of population.[13] 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 often regarded as 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. For example, voters living in rural counties, where the agricultural sector is the primary economic driver, have voted predominantly for Republicans (Gelman, Shor, Bafumi and Park, 2005).

Table 3 summarizes the US presidential election results in 2016 and 2020. In 2016, the Republican candidate, Donald Trump, defeated the Democratic candidate, former secre-

[13] 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.

Table 3: Presidential Election Results Comparison between 2016 and 2020

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

Notes: Total voter turnout rate refers to the percentage of eligible voters who cast a ballot in an election. The popular vote rate denotes the percentage of votes cast for a candidate by voters in the 50 states and Washington, D.C. The electoral votes refer to a vote cast by a member of the electoral college. Elector 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 a congressional district 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.

tary of state Hillary Clinton (304 electoral votes for Trump; 227 electoral votes for 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). The election saw the highest voter turnout since 1900 (66.7% voter turnout rate). Although Biden won the largest 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, raised 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. Broadly speaking, Democrats were considered to have an advantage on those voting issues, which contributed to a victory for Biden.

Among the several issues brought up in the 2020 presidential election, the US-China trade war was not unilaterally favorable to one party. Trump pursued a protectionist trade policy by imposing tariffs on foreign products, especially targeting China in early 2018. Potentially, Trump 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, 2020; Bown, 2020; Fajgelbaum, Goldberg, Kennedy and Khandelwal, 2020). In response to the retaliatory tariffs, Trump 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, 2020).

3 Data Overview

In our empirical analysis of presidential elections, we examine county-level changes between 2016 and 2020 in the two-party vote share for the Republican candidate. 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.[14]

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.[15] 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 et al., 2019; Autor et al., 2020), we compute the two-party vote share for the Republican candidates, which is defined as the number of Republican votes divided by the total votes for Republican and Democratic candidates.[16]

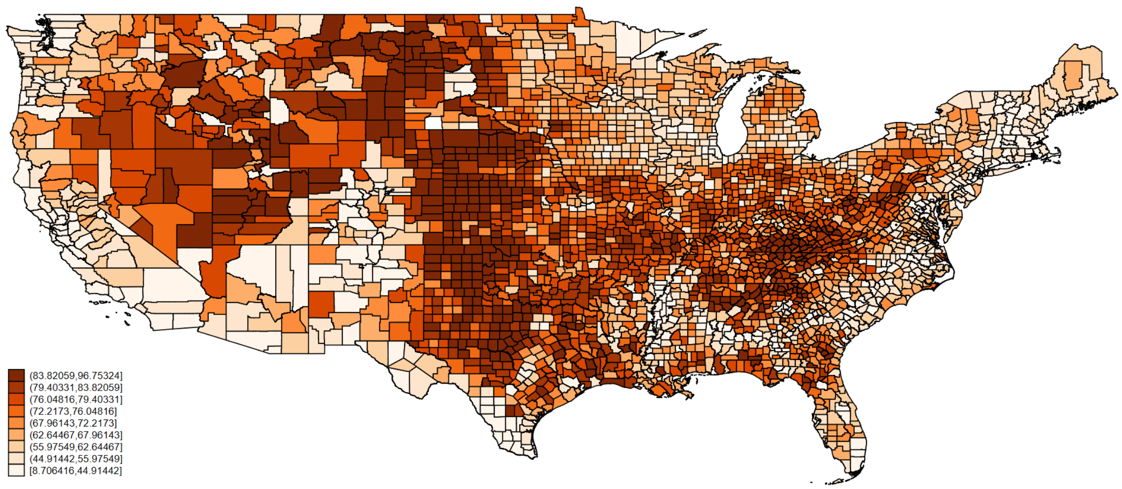
Figure 2 shows the county variation in the two-party Republican vote share in the 2016. In this map, a county is colored according to its position within the distribution. A darker orange indicates that a county frequently supports Republicans; a lighter orange indicates that a county frequently supports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

[14] 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.

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

[16] Since the 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. Independent city of Bedford, Virginia (51515) became part of Bedford County, Virginia (51019) on July 1, 2013.

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



the Democratic Party.

In Panel A of Table 4, summary statistics on voting outcomes are presented. 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:

$$\text{Chn\_Ag\_TS}_c = \sum_{i \in I^{Ag}} \frac{V_{ic}}{V_i} \frac{TS_i^{US \to CHN}}{L_c} \tag{1}$$

where c refers to a county, i denotes a NAICS 3-digit industry, and I^{Ag} is the set of agricultural industries. V_{ic} denotes the market value of agricultural products sold in industry i and county c; V_i denotes the total market value of agricultural products sold in industry i in the US; $TS_i^{US \to CHN}$ means the China's retaliatory tariff shock that falls on industry i; and L_c denotes the total population in county c. The data on 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.

The China's retaliatory tariff shock that falls on NAICS industry i, $TS_i^{US \to CHN}$, was constructed as follows. First, we use the information on China's agricultural retaliatory

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	1,386,997	3,643,117	0	90,885,032	US$
China's Ag. Ret. Tariff Shock per person	85	175	0	2,346	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	4,640,086	10,739,502	-181,210,288	63,388,088	US$
Net MFP per person	450	1,112	-4,693	12,041	US$

Notes: 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 the 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 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, Net $\text{MFP}_c \equiv \text{MFP}_c - 2 \times \text{Chn\_Ag\_TS}_c$.

tariffs collected by Bown (2020).[17] Let $\Delta(\tau_p^{US\rightarrow CHN})$ 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 $X_p^{US\rightarrow CHN}$ be the value of trade flows for product p from US to China in 2017. Third, let $TS_p^{US\rightarrow CHN} = X_p^{US\rightarrow CHN} \times \Delta(\tau_p^{US\rightarrow CHN})$ be the magnitude of tariff revenues that would be raised holding trade flows constant in 2017.[18] Last, using the HS-to-NAICS concordance table from the 2017 Census, we convert product level tariff shock, $TS_p^{US\rightarrow CHN}$, to NAICS industry level tariff shock, $TS_i^{US\rightarrow CHN}$.

We adopt the county-level measure of China's retaliatory tariff exposure per worker used in Blanchard, Bown and Chor (2019), but we modified their measure in order to answer our research question in the context of the agricultural sector. We use the county-level market value of agricultural products sold as a weight 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, the value of production is not

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

[18] Please refer to the "tariff shock" in Table 1.

necessarily proportional to employment (Fisher and Knutson, 2013).[19]

To overcome this issue, we adopt the county-level market value of agricultural products sold in 2017 to weight the county-level contribution to each agricultural industry, using the 2017 Census of Agriculture data developed by the USDA National Agricultural Statistics Service.[20] This dataset has some advantages over the 2016 County Business Patterns (CBP) county-level employment data used in Blanchard, Bown and Chor (2019). Unlike the CBP data, the 2017 Census of Agricultural data allows us to capture data for NAICS 111 (Crop Production) and NAICS 112 (Animal Production and Aquaculture). As noted in Blanchard, Bown and Chor (2019), the CBP data have missing-data issues for agriculture.[21] Because our study focuses on Chinese tariff shocks to US agricultural goods, using a proxy for the agricultural sector is likely to cause measurement errors. Further, for confidentiality reasons, the data have numerous observations marked as a letter code indicating 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. The 2017 Census of Agriculture data has fewer "class flags", which allows us to measure county-level production more precisely.[22]

Figure 3 shows the county variation in the shock caused by China's retaliatory tariffs per person. A darker blue indicates that 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, the Southeast, and California appear to have been hit hard by China's retaliatory tariffs.

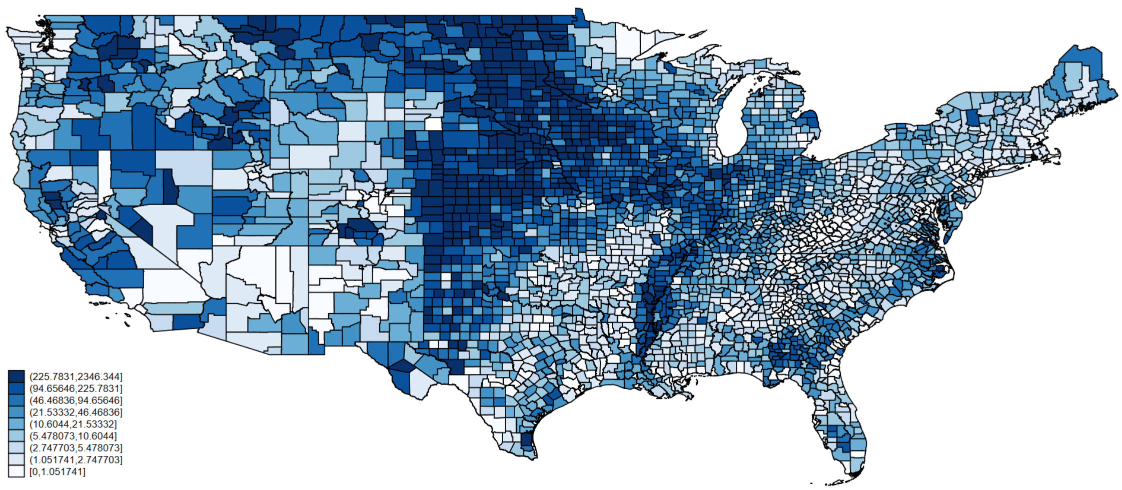
[19]For example, within the agricultural industry (i.e., NAICS 111), specialty crop production is more labor-intensive but less impacted by the Chinese agricultural tariff shock. However, non-specialty crops, such as soybeans, are less labor-intensive but more damaged by the Chinese retaliation. Also,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

[20]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.

[21]The CBP data does not 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)" for proxies for "Crop Production (NAICS 111)" and "Animal Production and Aquaculture (NAICS 112)", respectively.

[22]Regarding the missing values, the CBP reports a flag instead of an actual employment size for 1,382 out of 3,104 counties in the US under NAICS 2-digit 11 (Agriculture, Forestry, Fishing and Hunting) in 2017 (i.e., 45% data suppression rate). Note that the CBP does not report NAICS 3-digit industries for NAICS 111 (Crop Production) and NAICS 112 (Animal Production and Aquaculture). The 2017 Census of Agriculture data reports a flag only for 83 out of 3,112 counties for NAICS 111 industry and 82 out of 3,112 counties for NAICS 112 industry (a 2% data suppression rate). To minimize the measurement error for these suppressed production values, we replace them with the average value of the rest of the production values (i.e., the total production value in the US minus total production value for non-missing counties divided by the number of missing counties).

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



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 $85. There is substantial variation across counties: the lowest is zero and the highest is $2,346. The standard deviation is $175. In 40 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 Foreign Agricultural Service (USDA-FAS). We use the actual disbursement of Market Facilitation Program (MFP) data at the county-level.[23] The total actual disbursement of MFP1 in 2018 and 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, 2020). 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.[24]

[23]Permission to access the data was granted through an official arrangement between the authors and the USDA- FAS.

[24]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).

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.[25] First, as we discussed in 2.2, between 2018 and 2019 the MFP rate base, covered crops, and thus 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.[26] Second, the MFP payments are provided only for eligible applicants, who must satisfy legal conditions established by the USDA-FAS.[27] 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.[28]

Using the actual disbursement data at the county level, Figure 4 shows the county variation in the MFP payments per person. A darker red indicates that a county received more MFP payments; a lighter yellow 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.[29]

In Panel C of Table 4, summary statistics on agricultural subsidies are presented. On average, an MFP payment per person at the county-level is $619. There is a substantial variation across counties: from zero subsidy 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

[25] 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 (2020) 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.

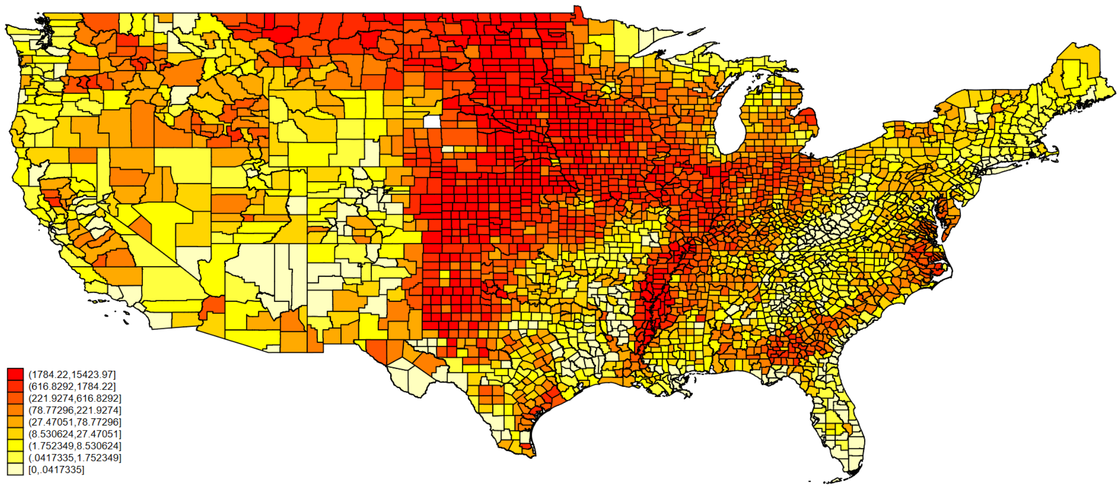
[26] A producer's total payment-eligible plantings are not allowed to exceed total plantings in the previous year. Also, MFP2 payments are limited to a combined $250,000 for non-specialty crops per legal entity, $250,000 for dairy and hog producers, and specialty crop producers.

[27] 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 their adjusted gross income from farming or ranching. Please refer to the following link for more details: https://www.farmers.gov.

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

[29] 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).

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



the American Community Survey (ACS) developed by the US Census Bureau, which compiles 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 (changes between 2012 and 2016).[30] The COVID-19 variables come from Covid Act Now (CAN).[31]

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 Nov 2, 2020, one day before Election Day.

[30]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. Please refer to the following link for more details: https://www.census.gov/programs-surveys/acs/about/acs-and-census.html

[31]Please refer to the following link for more details: https://covidcountydata.org/

4 Tariffs, Subsidies, and Political Targeting

In Section 4.1 we first conduct a simple correlation analysis of whether Chinese tariff retaliation, US agricultural subsidies, and the two-party Republican vote share in 2016 were associated with each other at the county level. In Section 4.2 we investigate whether the US agricultural subsidies relative to the Chinese retaliatory tariff exposure 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:

$$\text{Chn\_Ag\_TS}_c = \beta \text{RV}_c^{2016} + \psi_s + \varepsilon_c$$

where c denotes a county and s indicates state. Chn_Ag_TS_c is 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 year 2016.

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)	0.5710***	0.6651***			4.4381***	4.1510***
	(0.1278)	(0.1434)			(1.0564)	(1.2474)
Chinese Ag. Tariff Shock			7.0147***	6.7947***		
			(0.6732)	(0.7478)		
State FEs	No	Yes	No	Yes	No	Yes
Observations	3,112	3,111	3,112	3,111	3,112	3,111
R-squared	0.0520	0.2282	0.7658	0.7890	0.0489	0.2290

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

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 0.57 dollars per person. In column (2) of Table 5, we include state fixed effects. The coefficient is 0.67, suggesting that Republican-leaning counties seemed to be targeted by Chinese agricultural trade policy.[32]

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.

$$\text{MFP}_c = \beta \text{Chn\_Ag\_TS}_c + \psi_s + \varepsilon_c$$

where MFP_c measures actual disbursements of MFP payments.

In column (3) of Table 5, a one dollar per person increase in Chinese agricultural tariff shock is associated with an MFP payment increase of 7.01 dollars per person. In column (4) of Table 5, we include state fixed effects and found the coefficient to be 6.79.

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. First, in columns (3) and (4) of Table 5, the coefficients are both greater than one. We interpret this result to mean that the payment of MFP per person is greater than the tariff shock per person. Second, in Figure 5, conditional on the same magnitude of the tariff shock, counties receive different levels of MFP payments. This suggests that there exist counties that receive more MFP payments than the tariff shock, and vice versa.[33]

To the extent that tariff shocks are positively correlated with MFP subsidies, we would also expect that Republican-leaning counties attracted more MFP subsidies.[34] We conduct the following correlation analysis to study the relationship between MFP subsidies and the Republican vote share in 2016:

$$\text{MFP}_c = \beta \text{RV}_c^{2016} + \psi_s + \varepsilon_c$$

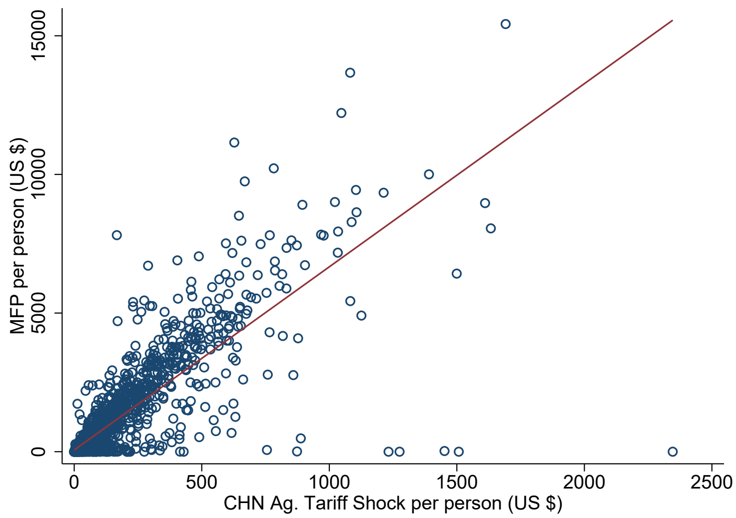
In column (5) of Table 5, a one percentage point increase in Republican vote share is

[32] This result is consistent with recent findings by Fetzer and Schwarz (2020), Fajgelbaum, Goldberg, Kennedy and Khandelwal (2020), and Kim and Margalit (2021) where those papers noted that tariff retaliation was directly targeted to areas that swung to Donald Trump in 2016.

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

[34] 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.

Figure 5: Market Facilitation Program and Chinese Agricultural Tariff Shock



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

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.

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 pure positive associations among Chinese retaliatory tariffs, MFP payments, and Republican vote share do not necessarily mean that the distribution of the MFP payments was politically considered to win the 2020 presidential election. Since Republican counties are more agriculturally oriented, it seems natural that those counties received more MFP payments, regardless of political orientation. Instead, we develop a new measure–i.e., the Net MFP–by calculating the difference between the MFP payment and the damage of the Chinese agricultural retaliatory tariff at the county level to assess the political economy of the 2020 presidential election.

For each county c, the "Net MFP" is defined by calculating the difference between an

MFP payment and an adjusted Chinese agricultural retaliatory tariff as follows:

$$\text{Net MFP}_c \equiv \text{MFP}_c - \kappa \times \text{Chn\_Ag\_TS}_c \tag{2}$$

where $\kappa > 0$. The above measure can capture combined trade policies (i.e., 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 Chinese retaliatory tariff shock is comparable to MFP.[35]

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. As China committed to purchase 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 the Chinese agricultural tariff shock has declined, especially in the agricultural sector (see Figure 1).[36]

We first check whether our new measure is correlated with Republican vote share in 2016 across US counties. Figure 6 summarizes the relationship. Interestingly, counties more supportive of the Republican Party see an increase in the Net MFP, which suggest 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 to detect a positive or negative pattern between the two unless there were political motivations.[37]

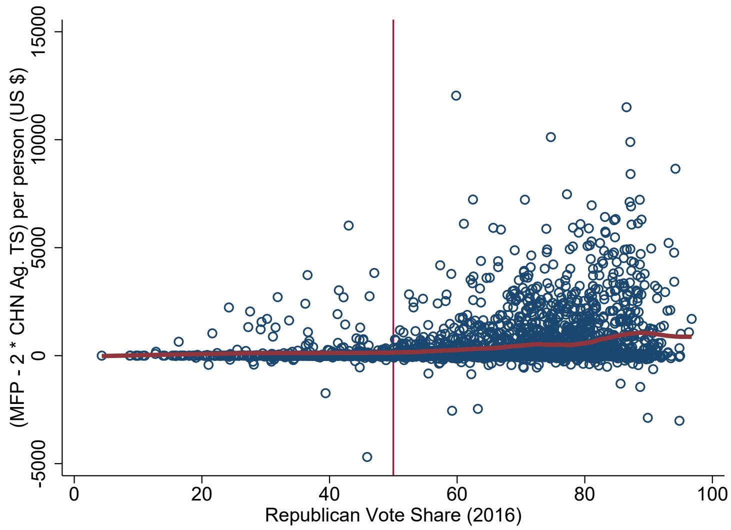
Does this result mean the distribution of MFP payments was strategically motivated to win the 2020 presidential election? Or does this result indicate that Trump allocated rents

[35] Note that the magnitude of Chn_Ag_TS$_c$ is based upon the magnitude of tariff revenues that would be raised holding trade flows constant in 2017 (i.e., annual values).

[36] In Panel D of Table 4, summary statistics for "Net MFP" are presented. On average, the Net MFP at the county-level is \$450. There is a substantial variation across counties: the lowest is -\$4,693 and the highest is \$12,041. The standard deviation is \$1,112.

[37] As we discussed in Section 2.2, many raised concerns about 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 (2). Second, our analysis is based on all US counties, while previous studies conducted state-level (and some county-level) analysis. Third, we use the actual disbursements of MFP payments, while previous studies used estimated MFP payments.

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



Notes: The vertical axis represents "Net MFP"; the horizontal axis represents Republican vote share in 2016. We perform a locally weighted regression of "Net MFP" on 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.

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 those swing states. Lindbeck and Weibull (1987) propose that parties target policy benefits to ideologically neutral voters since the marginal utility of consumption is decreasing, 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 presidential election. However, the increasing Net MFP pattern (captured by the lowess smoother) appears to support the core voter model, implying that Trump allocated rents in exchange for political patronage.

5 Tariffs, Subsidies, and the 2020 US Presidential Election

Up until now, 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. We now analyze how Chinese agricultural trade policy and US agricultural subsidies together affected the 2020 US presidential election. Our analysis progresses through several steps: by examining the impact of the Chinese retaliatory tariff shock on the 2020 election in Section 5.1; by investigating the role of US agricultural subsidies in the 2020 election in Section 5.2; by assessing the net effect of both the tariff shock and the agricultural subsidy on the 2020 election in Section 5.3; and by assessing the impact of the US-China trade war on the 2020 presidential election across political competitiveness bins in Section 5.4.

5.1 Did Chinese Retaliatory Tariff Shock Affect the 2020 Election?

We evaluate the impact of Chinese Retaliatory Tariff Shock on the 2020 US Presidential election. First, we estimate the following first-difference (FD) regression model:[38]

$$\Delta \text{RV}_c^{2020-2016} = \beta \text{Chn\_Ag\_TS}_c + \gamma \Delta \text{RV}_c^{2016-2012} + \delta \text{RV}_c^{2016} + \theta X_c + \psi_s + \varepsilon_c \tag{3}$$

where c denotes county, $\Delta\text{RV}_c^{2020-2016}$ refers to the change in the two-party Republican vote share between 2016 and 2020 presidential elections, and Chn_Ag_TS_c is China's agricultural retaliatory tariff shock, which is defined as a county's average exposure to China's retaliatory tariffs on US agricultural exports per person. Note that when T = 2, the 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 charactericistics.

$\Delta\text{RV}_c^{2016-2012}$ is the change in the two-party Republican vote share between 2012 and 2016 presidential elections, which controls for a pre-existing trend in the change in the two-party Republican vote share. RV_c^{2016} refers to the two-party 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 (3) 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 trade policies after purging existing voting patterns and pre-existing trends at the county level.

[38]Later, we include the MFP variable in the regression and evaluate the role of MFP in the 2020 US presidential election.

Even after accounting for endogeneity by controlling for time-invariant county characteristics through the first-differencing, the pre-exsiting trends, and the existing voting patterns, there remain some concerns to claim causality in our approach (e.g., reverse causality and omitted variable bias). To be clear, the reverse causality is not an issue at all – the 2020 election outcomes could not influence the China's retaliatory tariff shock and the corresponding US agricultural subsidies (see Section 2 for more details). The only remaining concern to establish causality is the issue of potentially confounding omitted variables. Hence, our approach is to add potentially confounding variables to alleviate concerns regarding the endogeneity issue.

To control for potentially confounding factors that may simultaneously affect US and Chinese agricultural policies and the change in the two-party Republican vote share between 2016 and 2020, we include a set of county-level control variables, X_c.[39] Most importantly, the COVID-19 pandemic was a key issue that shaped the 2020 presidential election. We include COVID-19 cumulative deaths (and cases) per 1,000 population as of Nov 2, 2020, just one day before Election Day, in equation (3). Another pattern people noticed in the 2020 presidential election was the movement 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 (3) to control for this movement. In a similar vein, population share and its change for black population can control for "Black Lives Matter" movement. Many commentators suspected 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 are 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 health insurance coverage rate and its change in equation (3). X_c also includes the (log) median and mean household annual incomes, labor force participation rate, the unemployment rate, population share by four education levels, seven age bins, and voting age population share. ψ_s are state fixed effects, which can control for state-specific trends.[40] Hence, the identification of our key coefficient is based on within-state and between-county variations. We weight counties by county's total voting-age population in year 2016. We cluster standard errors at the state level to allow for errors to be correlated within states.

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

[40] Note that the state fixed effects in the first-difference (FD) model in equation (3) is equivalent to state by time fixed effects in the fixed effects estimation model.

Table 6: Republican Vote Share and Retaliatory Tariff Shocks

Dependent Variable:	Δ Rep. Vote Share (2020 - 2016)				
	(1)	(2)	(3)	(4)	(5)
Chinese Ag. Tariff Shock	0.0039**	0.0056**	0.0060***	0.0009	0.0004
	(0.0019)	(0.0023)	(0.0018)	(0.0016)	(0.0014)
Δ Rep. Vote Share (2016 - 2012)			0.3564***	0.1998***	0.1738***
			(0.0480)	(0.0428)	(0.0405)
Rep. Vote Share (2016)			-0.1240***	-0.0751***	-0.0719***
			(0.0158)	(0.0113)	(0.0090)
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	0.0039	0.2348	0.5124	0.8114	0.8427

Notes: The dependent variable is the change in the two-party Republican vote share 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 county's total voting-age population in year 2016. Standard errors are clustered at the state level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6 presents the estimation results. In Column (1), we start by relating the change in Republican presidential vote share between 2016 and 2020 and Chinese agricultural tariff shock without any control variables. The coefficient is 0.0039 and is statistically significant at the 5 percent level. In Column (2), we incorporate state fixed effects into the regression equation and the result is almost unchanged. Column (3) adds a pre-existing trend variable–i.e., the change in the Republican vote share between the 2012 and 2016 US presidential elections, and the Republican vote share in the 2016 presidential election. The coefficient of 0.0060 is still positive and statistically significant at the 1 percent level. Quantitatively, a one standard deviation (see Table 4) increase in exposure to retaliatory tariffs is associated with about a 1.05 percentage point (0.0060×175) increase in the Republican vote share. In Column (4), we add county controls in levels. The coefficient becomes negative and statistically insignificant. Column (5) adds county controls in changes and the result unchanged. Although we found the coefficient to be statistically insignificant in the full set of control variables in Column (5), the impact of retaliatory tariffs on the 2020 presidential election could have been mitigated by the MFP subsidy (i.e., an omitted variable bias). Hence, the estimated coefficient can be upward biased conditional on a positive correlation between the MFP subsidy and the tariff shock.

5.2 Did the MFP Subsidy Play a Role in the 2020 Election?

We then incorporate the MFP variable into the equation (3) to analyze how it mitigated Chinese retaliatory tariff shocks and impacted the 2020 presidential election by estimating the following regression:

$$\Delta \mathrm{RV}_c^{2020-2016} = \beta_1 \mathrm{Chn\_Ag\_TS}_c + \beta_2 \mathrm{MFP}_c + \gamma \Delta \mathrm{RV}_c^{2016-2012} + \delta \mathrm{RV}_c^{2016} + \theta X_c + \psi_s + \varepsilon_c \quad (4)$$

where MFP_c is market facilitation program payments in county c.

Table 7: Republican Vote Share, Retaliatory Tariff Shocks, and MFP

Dependent Variable:	Δ Rep. Vote Share (2020 - 2016)				
	(1)	(2)	(3)	(4)	(5)
Chinese Ag. Tariff Shock	0.0030	-0.0017	0.0024	-0.0066***	-0.0059***
	(0.0026)	(0.0049)	(0.0038)	(0.0023)	(0.0020)
Market Facilitation Program	0.0001	0.0011*	0.0005	0.0010***	0.0009***
	(0.0003)	(0.0005)	(0.0004)	(0.0002)	(0.0002)
Δ Rep. Vote Share (2016 - 2012)			0.3551***	0.1975***	0.1724***
			(0.0484)	(0.0421)	(0.0399)
Rep. Vote Share (2016)			-0.1236***	-0.0771***	-0.0732***
			(0.0159)	(0.0112)	(0.0084)
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	0.0039	0.2387	0.5133	0.8144	0.8448

Notes: The dependent variable is the change in the two-party Republican vote share 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 year 2016. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7 presents the estimation results. We repeat the regression analysis of Table 6 with the same steps. Across all columns in Table 7, the impact of the Chinese agricultural tariff shock on the two-party Republican vote share becomes smaller after controlling for the MFP variable relative to the previous estimation that did not control for the MFP variable. This confirms that the MFP subsidy and tariff shock are positively correlated and therefore the previous estimation suffers from the omitted variable bias. Most important, after including the MFP variable with a full set of controls in Column (5), we find that Chinese retaliatory tariff negatively affects the Republican vote share and that the MFP payments positively affect the Republican vote share.

Quantitatively, using the coefficient (-0.0059) in Column (5), a one standard deviation (see Table 4) increase in exposure to retaliatory tariffs is associated with about 1.03 percentage points (-0.0059 $\times$ 175) decrease in Republican vote share. We found the MFP coefficient of 0.0007 in Column (5), which is statistically significant at the 1 percent level. Quantitatively, a one standard deviation (see Table 4) increase in exposure to MFP is associated with about 1.25 percentage points (0.0009 $\times$ 1,387) increase in Republican vote share. These results appear to mean tariffs induced a shift toward the Democratic candidate, while MFP induced a shift toward the Republican candidate.

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

We now combine those two trade policies 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? One scenario is that although the MFP partially mitigated the negative tariff shock, China's retaliatory trade policy still hurt Republican-leaning agricultural counties and led to a decline in Republican vote share. One second scenario is that the US agricultural subsidy outweighed the Chinese retaliatory tariff, resulting in an increase in Republican vote share. We estimate the following equation to answer the question:

$$\Delta \mathrm{RV}_c^{2020-2016} = \beta \mathrm{Net\ MFP}_c + \gamma \Delta \mathrm{RV}_c^{2016-2012} + \delta \mathrm{RV}_c^{2016} + \theta X_c + \psi_s + \varepsilon_c$$

where $\mathrm{Net\ MFP}_c = \left(\mathrm{MFP}_c - \kappa \times \mathrm{Chn\_Ag\_TS}_c\right)$. Our coefficient of interest is β, which measures the impact of both trade polices on the change in the two-party Republican vote share between 2016 and 2020 US presidential elections.

Table 8 shows the estimation results by repeating the regression analysis of Tables 6 and 7 with the same steps. Across all columns in Table 8, the impacts of Net MFP on the two-party Republican vote share are all positive and statistically significant at the 10 percent level. This supports the second scenario in which the US agricultural subsidy, which was intended to mitigate the Chinese retaliatory tariff, turned out to overcompensate US voters that led to an increase in Republican vote share. Quantitatively, a one standard deviation (1,112) increase in exposure to net MFP is associated with about a 0.44 percentage point (0.0004 $\times$ 1,112) increase in Republican vote share.

One might argue that Chinese retaliatory tariff may have affected more than two times ($\kappa = 2$ in equation (2)) the annual damage (i.e., the magnitude of tariff revenues that would be raised holding trade flows constant in 2017) because the losses from the trade shock might also affect the longer-term costs of adjusting for the market disruption, managing surplus commodities, or developing new trade partners (USDA, 2019). While the

Table 8: Republican Vote Share and Net MFP

Dependent Variable:	Δ Rep. Vote Share (2020 - 2016)				
	(1)	(2)	(3)	(4)	(5)
Net MFP	0.0005*	0.0011***	0.0009***	0.0006***	0.0004**
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Δ Rep. Vote Share (2016 - 2012)			0.3574***	0.1945***	0.1697***
			(0.0488)	(0.0419)	(0.0397)
Rep. Vote Share (2016)			-0.1228***	-0.0757***	-0.0721***
			(0.0157)	(0.0109)	(0.0083)
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	0.0029	0.2387	0.5123	0.8133	0.8438

Notes: The dependent variable is the change in the two-party Republican vote share 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 year 2016. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

total US agricultural export value to China in 2020 has recovered to its level in 2017 (see Figure 1), we use alternative values of κ from 3 to 10 to check if our results are robust to potential retaliatory tariff damages in the long run. In Appendix Table A.4, we find that our result is still robust to the longer-term potential retaliatory tariff damages.

As the regression results in Table 8 clearly show, China's retaliation to undermine US farmers led ultimately to increase support for the Republican Party.[41] China's retaliation tariffs disproportionately targeted the agricultural sector, which intended to harm the politically influential interest group, American farmers, in the US. Those retaliation tariffs appeared to aim at easing trade restrictions that were imposed against China.[42] However, rather than lessening the tension, President Trump went even further and subsidized US farmers through the MFP, which increased further the Republican vote share.

[41] 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.

[42] 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.

5.4 Treatment Heterogeneity

We now assess the impact of the US-China trade war on the 2020 presidential election across political competitiveness bins by estimating the following equation:

$$\Delta \text{RV}_c^{2020-2016} = \sum_b \beta_b \text{Net MFP}_c \times \mathbb{1}\{c \in I^b\} + \gamma \Delta \text{RV}_c^{2016-2012} + \delta \text{RV}_c^{2016} + \theta X_c + \psi_s + \varepsilon_c$$

where $\mathbb{1}\{c \in I^b\}$ is an indicator variable that equals one if county c belongs to competitiveness bin I^b in which $b = \{$"Solid Republican state," "Swing state," "Solid democratic state."$\}$ "Solid Republican state" maintained a two-party Republican vote share > 55 percent in the 2016 election (1,357 counties); "Swing state" maintained a two-party Republican vote share between 45 percent and 55 percent in the 2016 election (1,388 counties); "Solid Democratic state" maintained a two-party Republican vote share < 45 percent in the 2016 election (367 counties).

Table 9 shows the estimation results. In Column (5) where we include a full set of control variables, the impacts of Net MFP on the two-party Republican vote share across competitiveness bins (i.e., "Solid Republican state," "Swing state," and "Solid Democratic state") are all positive and statistically significant at the 10 percent level. In order to derive comparable effects across the three groups, we multiply the average Net MFP by the coefficient in each group. In "Solid Republican state," the average exposure to Net MFP is a 0.27 percentage point (0.0004 $\times$ 677) increase in Republican vote share; in "Swing state," a 0.09 percentage point (0.0003 $\times$ 292) increase; in "Solid Democratic state," a 0.19 percentage point (0.0009 $\times$ 210) increase. The impacts are most pronounced in solidly Republican states and weakest in swing states.

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 Section 6.1. we first investigate whether those two polices affected the counterfactual aggregate election outcome–how many more Electoral College votes Republicans would have won in the absence of those two policies. Next, using the counterfactual analysis results, in Section 6.2 we look at how those two policies contributed to the partisan polarization, and in Section 6.3 at how they contributed to the rural-urban political polarization.

Table 9: Republican Vote Share and Net MFP by Competitiveness Bin

Dependent Variable:	Δ Rep. Vote Share (2020 - 2016)				
	(1)	(2)	(3)	(4)	(5)
Net MFP $\times$ Solid Republican	0.0004	0.0013***	0.0010***	0.0005***	0.0004**
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Net MFP $\times$ Swing States	0.0007*	0.0012***	0.0010***	0.0004*	0.0003*
	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0002)
Net MFP $\times$ Solid Democrat	0.0006	-0.0001	-0.0001	0.0012*	0.0009*
	(0.0006)	(0.0008)	(0.0007)	(0.0006)	(0.0005)
Δ Rep. Vote Share (2016 - 2012)			0.3588***	0.1935***	0.1692***
			(0.0490)	(0.0421)	(0.0400)
Rep. Vote Share (2016)			-0.1226***	-0.0761***	-0.0724***
			(0.0158)	(0.0109)	(0.0082)
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	0.0031	0.2398	0.5131	0.8136	0.8440

Notes: The dependent variable is the change in the two-party Republican vote share between the 2016 and 2020 US presidential elections. "Net MFP" is defined as the difference between an MFP payment and two times the Chinese retaliatory agricultural tariff, net $\text{MFP}_c \equiv \text{MFP}_c - 2 \times \text{Chn\_Ag\_TS}_c$. Following Autor, Dorn, Hanson and Majlesi (2020), "Solid republican state" maintained a two-party Republican vote share > 55 percent in the 2016 election (1,357 counties); "Swing state" maintained a two-party Republican vote share between 45 percent and 55 percent in the 2016 election (1,388 counties); "Solid democratic state" maintained a two-party Republican vote share < 45 percent in the 2016 election (367 counties). 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 year 2016. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

6.1 How many more Electoral College votes Republicans would have won in the absence of those two policies?

We compute the counterfactual county-level Republican vote shares under a scenario where the Chinese retaliation tariff and US agricultural subsidy are removed. By subtracting $\widehat{\beta}_b \times \text{Net MFP}_c$ from the actual Republican vote share for county c in each competitiveness bin I^b in the 2020 presidential election, we obtain the counterfactual Republican vote share (or Republican vote casts) for each county in each competitiveness bin where $\widehat{\beta}_b$ is from the full specification in Column (5) of Table 9. 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 A.5 presents the counterfactual two-party Republican vote share in the 2020 election. At the state level, we find that those two policies had no estimated 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.

6.2 Partisan Polarization

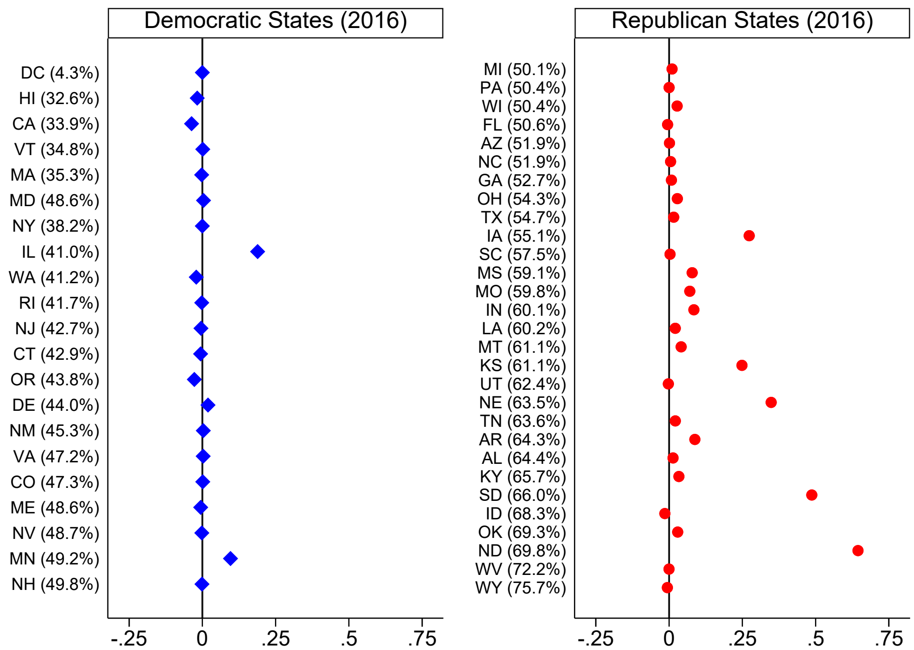
Although our counterfactual analysis shows that China's retaliatory agricultural tariff and the corresponding US agricultural subsidy had no estimated impact on the predicted number of Electoral College votes, we find evidence that those two policies unexpectedly contributed to exacerbating partisan polarization in the US. Figure 7 shows the implied effect of the net MFP on the two-party Republican vote share in 2020 at the state level. The implied effects were especially high in Republican states where the two-party 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 0.115 percentage point, with a range between -0.015 and 0.645. On the other hand, the implied effects were almost negligible in those solidly Democratic states where the two-party 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 -0.037 and 0.189. In particular, the implied effect of the net MFP on California, which was the top US agricultural state in agricultural sales in 2017, was negative with -0.037, meaning that after the implementation of those two policies the Democratic vote share increased in California in the 2020 US presidential election.

Our 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). In particular, our finding is close to that of Autor, Dorn, Hanson and Majlesi (2020), who unraveled how rising import competition contributed to the polarization of the US politics. However, to the best of our knowledge, there are still few empirical studies of the issue. We provide empirical evidence that US agricultural policy in response to the Chinese retaliatory trade policy heightened the partisan divide by contributing to the unexpected outbreak of the US-China trade war.

6.3 The Rural-Urban Political Polarization

We find further evidence that the unexpected outbreak of the US-China trade war unexpectedly exacerbated the rural-urban political polarization. Figure 8 presents the implied effect of the Net MFP on the two-party Republican vote share in 2020 at the metro, urban,

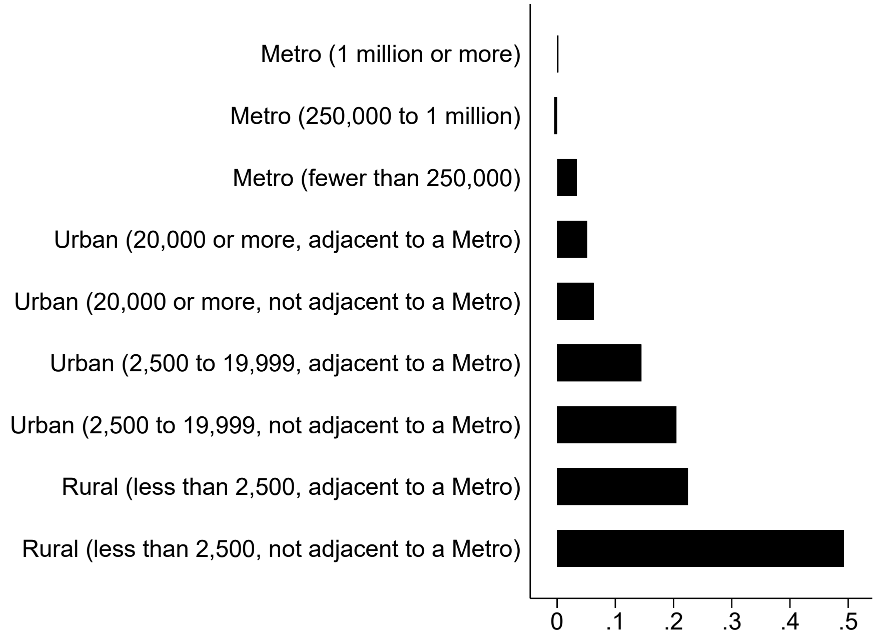
Figure 7: The Implied Effect of the Net MFP on Political Polarization in the 2020 Election



Notes: "Republican (or Democratic) States (2016)" refers to states where the two-party Republican vote share is great than 0.5 (respectively, less than 0.5) in the 2016 presidential election. The number in parentheses is the two-party 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 two-party Republican vote share (%) in the 2016 presidential election in each panel. The unit of measure on the horizontal axis is percent. Each dot means the implied change of 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 9. We aggregate the county-level point up to the state level.

and rural levels. We distinguish 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 up to each metro, urban, and rural category. In Figure 8, 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 two-party Republican vote shares are relatively small, ranging from -0.005% to 0.033%. In the four urban areas, the implied effects of the two-party Republican vote shares are slightly larger than in the metro areas, ranging 0.052% to 0.205%. In the two rural areas, the implied effects of the two-party Republican vote shares are larger than in the other areas, ranging from 0.225% to 0.493%.

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



Notes: 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 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 parentheses refers to the descripton of classification by each category. The estimates are calculated based on the point estimates from the full specification in Column (5) of Table 9. We aggregate the county-level point up to each rural-urban category. The unit of horizontal axis (the implied effect of the net MFP) is percent. Alaska is excluded.

Although the evidence of rural-urban political polarization in the US is strong, to the best of our knowledge the mechanism that created the two Americas–one urban and one rural–is not well understood (e.g., Fiorina and Abrams, 2008; McKee, 2008; Scala and Johnson, 2017). Although the rural-urban divide was not caused by the US-China trade war, we provide empirical evidence that the two countries' trade policies unexpectedly heightened it.

7 Conclusion

Retaliatory tariffs by China during the US-China trade war covered virtually all 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. While 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.

While it has been argued that the two countries' trade policies may have affected the 2020 presidential election, 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 often been unavailable to researchers at the 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 affect political outcomes.

Our core findings are as follows. The Net MFP was distributed disproportionately to the Republican base, implying that Trump 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.

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Appendix

Appendix A: Tables

Table A.1: U.S. Agricultural Exports to China from 2015 to 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**

Notes: Data come from US Census Bureau Trade. 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

Notes: Summary statistics across N = 3,112 counties. The variables in Panels A., B., and C. are from the US Census American Community Survey data in 2016 (5-Year estimates). The COVID-19 variables in Panel D. come from Covid Act Now (CAN). 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 16 years old and over population that is in the labor force. In Pannel C, some college includes both some college and associate's degree. 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 coverages.

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

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

Table A.4: Republican Vote Share and Net MFP: Robustness Check

Dep. Var.:	Δ Rep. Vote Share (2020 - 2016)								
	$\kappa = 2$	$\kappa = 3$	$\kappa = 4$	$\kappa = 5$	$\kappa = 6$	$\kappa = 7$	$\kappa = 8$	$\kappa = 9$	$\kappa = 10$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Net MFP	0.0004**	0.0005***	0.0006***	0.0007***	0.0008***	0.0009***	0.0008***	0.0007***	0.0006***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	3,111	3,111	3,111	3,111	3,111	3,111	3,111	3,111	3,111
R-squared	0.8438	0.8440	0.8443	0.8445	0.8447	0.8448	0.8447	0.8444	0.8441
State FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls Included: {Δ Rep. Vot. Share (2016 - 2012), Rep. Vot. Share (2016), County in Levels, and County in Changes}									

Notes: The dependent variable is the change in the two-party Republican vote share 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 2016. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: Counterfactual Two-Party 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	0.005	50.679
VT	31.701	0.001	31.699	FL	51.695	-0.005	51.700
MA	32.884	-0.002	32.887	TX	52.831	0.016	52.815
MD	32.971	0.004	32.967	OH	54.077	0.028	54.049
HI	34.967	-0.017	34.985	IA	54.183	0.273	53.910
CA	35.090	-0.037	35.127	SC	55.927	0.003	55.923
NY	38.264	0.000	38.264	KS	57.493	0.249	57.245
RI	39.490	-0.002	39.492	MO	57.836	0.071	57.765
CT	39.828	-0.006	39.834	IN	58.195	0.084	58.111
WA	40.075	-0.021	40.095	MS	58.380	0.079	58.301
DE	40.373	0.019	40.354	MT	58.397	0.041	58.356
IL	41.341	0.189	41.152	LA	59.464	0.021	59.444
OR	41.693	-0.027	41.720	NE	59.784	0.348	59.436
NJ	41.929	-0.005	41.933	UT	60.694	-0.003	60.696
CO	43.062	0.001	43.060	TN	61.828	0.021	61.807
NM	44.482	0.003	44.478	AL	62.911	0.013	62.898
VA	44.845	0.003	44.843	KY	63.200	0.033	63.167
ME	45.535	-0.006	45.541	SD	63.435	0.487	62.948
NH	46.252	-0.001	46.253	AR	64.212	0.088	64.125
MN	46.361	0.096	46.265	ID	65.877	-0.015	65.892
MI	48.586	0.010	48.576	OK	66.940	0.029	66.911
NV	48.777	-0.002	48.779	ND	67.217	0.645	66.573
PA	49.399	0.000	49.399	WV	69.799	0.000	69.799
WI	49.681	0.027	49.654	WY	72.480	-0.006	72.486
AZ	49.843	0.001	49.842				
GA	49.881	0.008	49.873				

Notes: "Republican (or Democratic) States (2020)" refers to states where the two-party Republican vote share is great than 0.5 (respectively, less than 0.5) in the 2020 presidential election. "Rep. Vote Share" refers to the two-party 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 NE and ME, respectively. States are ordered according to the two-party 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 9. We aggregate the county-level point up to the state level. "Counterfactual Vote Share" refers to the two-party Republican vote share (%) in the absence of the Chinese agricultural retaliatory tariff and US agricultural subsidy.