Partisanship in the Trump Trade War: Evidence from County-Level Crop Planting Data

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Abstract

In 2018, the US-China trade war drove down the price of many US agricultural goods. While many farmers responded by planting alternative crops instead, others continued planting the low-value crops, with a high cost to their bottom line. Why did some farmers disregard their own economic interests and plant low-value crops during the trade war? We argue that political preferences partially drove farmer behavior. Matching geo-referenced crop data to product-level sanctions lists from China, we calculate county-level changes in planting of crops affected by the tariffs. We find that counties with a higher Trump vote-share in the 2016 election were significantly less likely to change planting decisions due to the trade war. This suggests that partisanship may affect the economy more broadly than previously realized.

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1 Introduction

A growing literature on affective polarization has found that ideological preferences can spill over into economic behavior. Much of this work focuses on the social aspect of economic decisions, comparing people's reactions to in-group versus out-group individuals (Gift and Gift 2015; Michelitch 2015) or companies (Panagopoulos et al. 2020; McConnell et al. 2018). Scholars have found that partisan homophily can play a large role in the decision to do business with others. However, the mechanisms behind these social preferences, and therefore their generalizability, remain unclear. Additionally, much of the evidence for the phenomenon is either self-reported or reflects low-stakes survey environments. Is this literature simply picking up on a form of social homophily, in which partisans prefer to support their own in-group (Mutz, 2006)? Or does the effect of partisanship on economic behavior extend to non-relational economic decisions, such as firms' decisions to produce certain goods? This is an important question in understanding the effect of polarization on the economy as a whole. It is one thing to suggest that partisans are willing to take on economic costs in order to reward or punish in-group or out-group individuals. However, the total societal costs of partisanship are much higher if partisans are also willing to take on economic costs in business decisions that do not affect their social interactions at all.

The mechanisms underlying partisan economic decisions have been debated, but there is almost certainly some combination of in-group favoritism (McConnell et al., 2018) and out-group antipathy (Gift and Gift, 2015) driving partisan behavior. Even less is known about how individuals behave when there is no group at all. There is some evidence that partisanship may affect micro-level decisions that are only tangentially related to politics. For example, the decision to install solar panels (Mildenberger, Howe and Miljanich, 2019), offer controversial medical procedures (Hersh and Goldenberg, 2016), physically distance during a pandemic (Gollwitzer et al. 2020), and fund social services (Metzl, 2019) can affect economic well-being and can be linked to partisan and political cues. The economic extent of such behaviors is not well explored.

We argue that even absent the element of in-group or out-group cooperation, Americans' economic behavior follows partisan patterns. Americans are willing to take on economic costs for their partisanship even absent social interactions; therefore, homophily does not fully explain partisanship in economic behavior. We find evidence that when partisan elites cue support for costly business decisions, partisan business owners will be more likely to carry out those decisions despite the costs. Such a practice need not serve to benefit an in-group or harm an out-group. This suggests that partisanship may affect a greater variety of decisions than other studies may have considered.

We test this theory on the case of the US-China trade war spearheaded by President Donald Trump in 2018. Because the trade war largely affected the agricultural sector, we examine farmers' responses to price shocks caused by China's retaliatory tariffs. Rather than rely on self-reported preferences, we are able to objectively measure firms' (in this case, farms') responses to the trade war using geo-referenced satellite imagery data from the US Department of Agriculture (USDA). We find evidence that farmers took partisan cues when making business decisions during the trade war. Counties that heavily supported Donald Trump in the 2016 Presidential election were less likely to stop planting crops that were negatively impacted by Chinese tariffs. This is despite the fact that many of these crops plummeted in value.[1] In contrast, farms located in counties with low Trump vote-share significantly reduced their planting of these tariffed goods, supporting their economic bottom line. Political preferences, not just economic well-being, appeared to factor in to farmers' planting decisions.

This paper integrates trade literature with the American politics literature on affective polarization (Mason 2015, 2018; Iyengar and Westwood 2015; Iyengar, Sood and Lelkes 2012). Similar to recent work, we find that economic preferences tend to mirror effect toward co-partisans. We extend these results to the realm of international political economy, finding that partisanship and ideology can play a role in individuals' decision-making in the trade

[1] Soybean prices, for example, decreased by 10-20% over the following year (Durkin, 2019).

realm as well.

Finally, this particular case is important in the context of rising import competition from China. The so-called "China Shock" of the mid-1990s was well known to have domestic political outcomes in the United States (Autor, Dorn and Hanson 2013; Feigenbaum and Hall 2015; Kuk, Seligsohn and Zhang 2018; Autor et al. 2020). The consensus is that exposure to import competition from China introduced a negative and lasting impact on local economies in the US, thereby increasing support for Republicans and protectionist trade policies. We build on more recent work, which has more directly examined domestic political responses in the context of the US-China trade war (Blanchard, Bown and Chor 2019; Kim and Margalit 2021; Chyzh and Urbatsch 2021).

In the remainder of this paper we develop and test a theory of partisan economic behavior during the US-China trade war. In Section 2, we further expand upon the motivation of the paper by examining data from the US-China trade war. In Section 3, we develop the theory, drawing from literature on affective polarization and economic behavior. In Section 4, we introduce the original data that we compiled by matching product-level lists of Chinese tariffs with remote sensing data from USDA and county-level voting records. We then test the theory on those data through both a cross-sectional analysis and a panel difference-in-differences design. Finally, we conclude with a consideration of the larger implications of this research. We suggest that future research could more deeply determine the ideological dynamics of firm behavior.

2 The US-China Trade War

In March 2018, the United States increased tariffs on Chinese steel and aluminum products, following previous year's investigations by the Department of Commerce under Section 232 of the Trade Act of 1974, and the United States Trade Representative under Section 301 of Trade Act of 1974. China quickly responded by imposing retaliatory tariffs on a wide variety of US products including aluminum, pork, fruits, and nuts. This led to a full-fledged trade war between the two countries throughout 2018 and 2019, each imposing up to fifty billion dollars worth of tariffs to the other. Specifically, China's retaliation involved adding 25 percent tariffs on US goods including *soybeans*, the most valuable agricultural product that the United States sells to China (Sheldon, 2019).

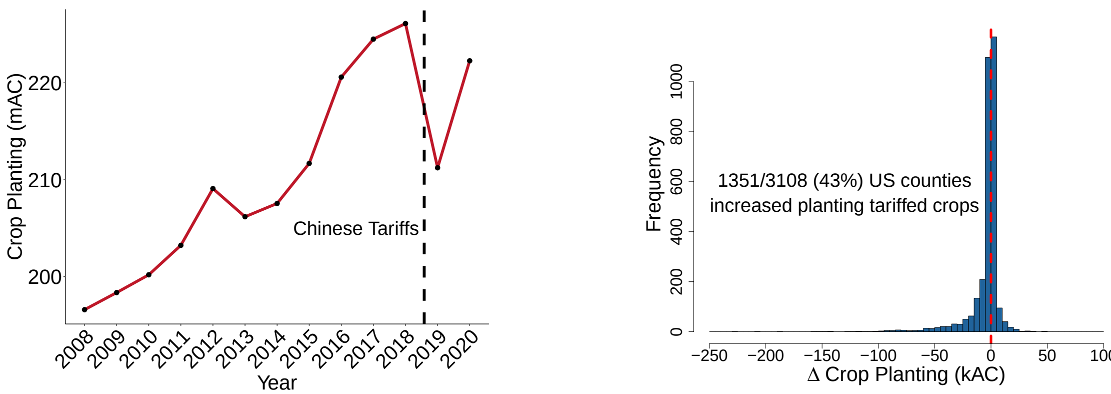
The US agricultural industry suffered severe economic losses during years of the US-China trade war. US farms' sales to China plummeted, going down from nineteen billion US dollars in 2017 to nine billion US dollars in 2018 (McCrimmon, 2020). Farm bankruptcies also increased by 24% in 2019 compared to those of the previous year (Lobosco, 2019). Moreover, the expectation that the trade war may last longer has grown after the two countries exchanged additional waves of tariffs between July and September 2018.

As would be expected, the uncertainty in sales and export price drop from the tariff shock prompted many US farmers to switch planting from dominant crops like soybeans and corn, to other minor crops that were not targeted by Chinese tariffs. However, not all farmers reacted identically to the tariffs. Figure 1 shows that while there was a steep overall decline in crop planting in 2019 that were subject to Chinese tariffs, a significant variation exists in how farmers reacted. In fact, about 42% of US counties *increased* planting of crops that were targeted by China's retaliatory tariffs, compared to the previous year.[2]

Why did some farmers respond in a way that could worsen their economic loss during the trade war, while others did not? The variation in crop planting during the US-China trade war may be explained through agriculture's unique characteristics. Unlike the manufacturing sector, production in agriculture relies directly on weather conditions and the quality of soil. Thus, where a farm locates itself determines the type and the amount of crops that a farmer can plant, and the farmer's response to unexpected price shocks.

Another way to explain this puzzling variation in farmers' crop planting behavior is to consider the role of agricultural subsidies distributed during the trade war. The US has long been a user of subsidies to assist the agricultural industry to manage economic downturns.

[2] Appendix B shows the variation of tariffed crops and soybean planting changes in 2019. For geographical distribution of such changes, see Appendix C3.



(a) Trend in Tariffed Crop Planting

(b) ΔCounty-level Planting in 2019

Figure 1. Changes in Tariffed Crop Planting in the United States. This figure displays planting trends and changes of crop planting (in million acres and %) that were targeted by Chinese tariffs in 3,108 US counties. Data is from the US Department of Agriculture's CropScape Crop Data Layers (CDL). The CDL does not provide data on Alaska and Hawaii regions, thus we exclude these two states from our analysis. Panel (a) displays a steep decline in crop planting (in million acres) in 2019 that were targeted by the 2018 Chinese tariffs, which bounces back in 2020. Panel (b) shows that about 43% of US counties have increased planting of such tariffed crops in 2019. Appendix D provides a complete list of crops that were subject to Chinese tariffs.

Building on existing subsidies, the Trump administration launched the "Market Facilitation Program (MFP)", a massive bailout program to offset economic losses that the agriculture industry experienced throughout the trade war. In 2018, roughly about 8.6 billion US dollars was paid to farmers through the MFP, while in 2019 the amount decreased to 6.6 billion US dollars. Though costly, the payments were not enough to prevent the large-scale bankruptcies mentioned above. Nonetheless, the large amount of agricultural subsidies may have been one factor that enabled the farmers to maintain their crop planting practice. Any empirical consideration of farmer behavior must therefore control for MFP subsidies.

Based on the above, one can expect that farmers' responses during the trade war reflected their economic calculations. However, anecdotal evidence also suggests that this puzzling behavior may also be related to farmers' partisan backgrounds, specifically to farmers' support for the Republican party, or president Trump himself (Evers-Hillstrom 2019). As one farmer put it, "We are the front-line soldiers getting killed as this trade war goes on... I'm unhappy and I think most of us are unhappy with the situation. But most of us understand the merits" (CNBC 2020). Farmers may have been abandoning their own well being for ideological reasons. In the following section, we develop a theory to explain these puzzling responses to the trade war.

3 Theory

We theorize that variation in farmer behavior during the trade war partially stems from farmers' political preferences. There are two potential ways that politics might impact business practices. First, politics might inform firms' expectations about the effects of the trade war on future profits. When the future is unknown, political beliefs can substitute for other forms of information. Second, farmers might be using planting decisions as a form of expressive action. Insofar as the planting of soybeans expresses loyalty to a political in-group, farmers could derive emotional and social benefits from expressing that loyalty. One of these mechanisms, or a combination of both, could lead farmers to change their planting behavior based on political beliefs.

It is no surprise that politics can affect beliefs. Farmers who are inclined to trust President Trump's policies might truly believe that these policies will lead to success. Therefore, they may find it worthwhile to accept small costs today in order to ensure those policies are successful. They may believe it to be a rational decision to continue business as usual, following the president's advice. The sooner that farmers believe the trade war will end, the more likely they will continue to plant tariffed crops.

Like any business owners, farmers take several factors into consideration when making business decisions. In choosing how to utilize scarce land resources, farmers consider present costs and future profits. The utility function of business owners, including costs and benefits of planting crops, is outlined in the equation below. The cost function includes factors such as the price of equipment and labor, as well as opportunity costs such as government subsidies that farmers may be giving up by planting and harvesting.[3] The benefit function includes productivity, or the volume of crops that are harvested, and the price that those

[3] In the case of the US-China trade war, these opportunity costs can be large: the government provided a lot of subsidies for farmers harmed by the trade war.

crops yield on the market. The part of this decision-making process that is most affected by tariffs is the price: tariffs decrease the value of crops on the market.

$$planting_t = productivity_{t+1} * price_{t+1} - costs_t$$

Note that the "benefits" side of the utility function requires a prediction about future productivity and price at time $t + 1$, while the costs are accrued at time t. This suggests that farmers' *expectations* about future benefits should play a large role in determining their business decisions. This should come as no surprise and is true of most any firm. Expectations about future productivity are motivated by weather conditions as well as farm-specific factors such as harvesting equipment and labor availability. On the other hand, expectations about the future *price* of the crop can be more subjective. This is where politically motivated beliefs could cause differences in behavior for different types of farmers.

Farmers' beliefs about the future price of their crops depend partially on their political expectations. Individuals who trusted President Trump to carry out policies that benefit the US economy might expect the trade war to end in short order, with a boost in prices for US goods. The trade war originated from a bout of presidential optimism, with the president initially tweeting "Trade wars are good, and easy to win" (Paletta, 2018). Therefore, it stands to reason that farmers' opinions of Trump could play a role in their own optimism about the trade war's success. Throughout 2018 and 2019, President Trump reassured farmers that the trade war would come to a swift end. He encouraged them to wait out the tariffs and continue planting as they had done before (Martin, 2019), ensuring them that prices on the tariffed goods would soon increase once again. Anecdotal evidence suggests that many farmers wanted to follow the president's lead and continued planting soybeans and other tariffed crops, despite rising bankruptcies (Lobosco, 2019).

It should come as no surprise that beliefs about economic realities can rely on partisan cues. Scholars have long argued that partisanship can serve as a "perceptual screen" through which people view economic facts (Campbell et al., 1960, 133). Elite cues are a strong driver of public opinion and behavior. Individuals often have little incentive or ability to determine policy preferences on every issue and often rely on elites to furnish them with well thought-out policy advice (Zaller et al. 1992; Page, Shapiro and Dempsey 1987). In the case of complex issues, such as foreign policy, the public often seeks out partisan cues to determine their opinions (Berinsky, 2007). This is especially true in trade policy, where people tend to lack interest and knowledge (Rho and Tomz, 2017).

Much research has concluded that perceptions about economic outlook are closely related to political opinions. Scholars since Bartels (2002) have noted that Republicans and Democrats report significantly different beliefs of the state of the economy, sometimes disagreeing on even the *direction* of economic trends. Some of these survey findings are almost certainly attributable to hyperpartisan "cheap talk," given that false perceptions decrease when individuals are provided a monetary incentive to get it right (Bullock et al. 2015; Prior, Sood and Khanna 2015). However, as Bisgaard (2019) notes, even when individuals are provided with the correct information about economic trends, they often manage to misattribute the causes.

Additionally, scholars using observational data have found that partisan economic beliefs affect consumer behavior. Gillitzer and Prasad (2018) and Gerber and Huber (2009) find that consumers are more likely to make larger purchases when their preferred party wins an election, which is in line with their professed optimism about the economy. This is partially due to expectations about the competence of preferred political leaders (Gerber and Huber, 2010). Less is known about the extent to which partisan preferences affect *producers'* decisions. One field experiment by McConnell et al. (2018) suggests that people produced differential results in a copyediting task when they believed they were doing work for co-partisans. But this hardly rises to the level of production that is relevant to the question of agricultural firms.

If partisanship and elite cues indeed affects consumers' economic decisions, then it stands to reason that leaders of agricultural firms may also use partisanship as a heuristic in making decisions about which crops to produce. In estimating the benefit side of their utility functions, farmers must make predictions under uncertainty. It is just such uncertainty that might lead them to rely on heuristic short-cuts, such as political cues.

Another explanation for political variation in farmers' behavior comes from the use of business practices as expressive signals. Instead of making instrumental cost-benefit calculations, some farmers could be reacting personally to the trade war and planting tariffed crops as a show of support for their preferred politician.[4] This need not even be wholly emotional: insofar as farmers reap social benefits for displaying their support for President Trump, they may be likely to show their support with their fields. When homeowners display lawn signs to express support for their preferred candidate, they reap social and emotional benefits from expressing political action (Makse and Sokhey, 2014). Research suggests that voters are more likely to take costly political actions—such as voting and protesting—when their friends and neighbors do so (Doherty and Schraeder 2018; Steinert-Threlkeld 2017; Bond et al. 2012; Gerber, Green and Larimer 2008). Planting of tariffed crops could be taking a form analogous to a giant lawn sign for some farmers.

Regardless of whether their motivations are instrumental, expressive, or social, farmers in areas more heavily supportive of Donald Trump are likely to make different planting decisions from farmers in non-Trump areas. Farmers who are more inclined to trust the president should be more likely to believe that (1) the trade war will be short-lived, (2) the trade war will put US farmers in a better position in the near future, and (3) friends and neighbors will be pleased to know of these beliefs. All of these beliefs indicate that farmers would be better off planting crops that are affected by the trade war, with the expectations that (1) these crops will not be affected for long, and (2) once the trade war ends, those who bet on a swift win will be better off than those who did not. The fact that some farmers decreased their reliance on crops affected by the trade war may *further* incentivize pro-trade-war farmers to increase their tariffed crop production: a decrease in supply elsewhere might

[4] This may be similar to incentives for expressive voting and other political actions (Schuessler, 2001).

make the potential profit even higher.

In contrast, those who are less ideologically inclined to follow Trump's lead may be more likely to believe that either (1) the trade war will not end soon, (2) the trade war will not result in a better economic position for US producers, or (3) friends and neighbors will not be pleased by an expression of support for the trade war. Once again, these beliefs affect farmers' utility calculations by shaping their expectations of future benefits. Instead of increasing production of tariff-affected crops, farmers whose ideological frameworks do not support pro-trade-war beliefs will be more likely to move production to other goods. These political expectations lead to the hypothesis below.

HYPOTHESIS 1 *The more extremely a population supports President Trump, the more likely its farmers will be to maintain their reliance on tariffed goods during the trade war.*

We test the above hypothesis of agricultural behavior and political preferences using observational data. Below, we outline the data that we collected and the methods we used to test this theory and determine the relationship between political preferences and costly economic behavior.

4 Data

To test our argument on the effect of partisanship on farmers' economic behavior during the US-China trade war, we link several political and economic databases. First, we collect annual county-level planting records from the US Department of Agriculture (USDA)'s Cropland Data Layer (CDL) Application Programming Interface (USDA-NASS, 2012). The CDL is a geo-referenced crop-specific land cover data based on satellite imagery.

Our outcome variables of interest are county-level measures of annual `crop planting` and `crop planting changes` of tariffed goods. We are particularly interested in whether or not farmers decreased their reliance on goods that experienced tariff shocks from China between 2018 and 2019. To construct these variables, we sum up annual volumes of tariff-affected crops, and also compute each of their annual differences. We use the list of items subject to the 2018 tariff announced by the Chinese Ministry of Commerce on June 16, 2018 to accurately calculate these numbers.[5] We then match each agricultural item on this list to the USDA CDL data based on agricultural product codes defined by the US Department of Agriculture (USDA).[6]

Matching the list of crops subject to Chinese retaliatory tariffs with the CDL's crop type list allows us to compute annual crop planting estimates at the county level. The first panel in Figure 2 presents the changes in planting of tariffed goods throughout the United States between 2018 and 2019.[7] The area outlined in blue represents the so-called "soybean belt" that includes the top 15 soybean-producing states in the US. We expect these states to be most heavily affected during the trade war.[8]

The main independent variable of interest is a county-level measure of support for president Donald Trump: `Trump's vote share` in the 2016 presidential election.[9] The second panel in Figure 2 displays Trump's vote-share at the county level. Notably, the median vote share is 66.4%. This is a result of the small rural county sizes in much of the Midwest and South. These small units are useful to our analysis —the smaller the unit of analysis, the closer we come to measuring farm-level behaviors.

Next, We consider a battery of economic factors to account for potential confounders of farmers' crop planting decisions in the pre-planting season. Annual county-level data for most of these factors are drawn from the US Bureau of Economic Analysis (BEA) regional eco-

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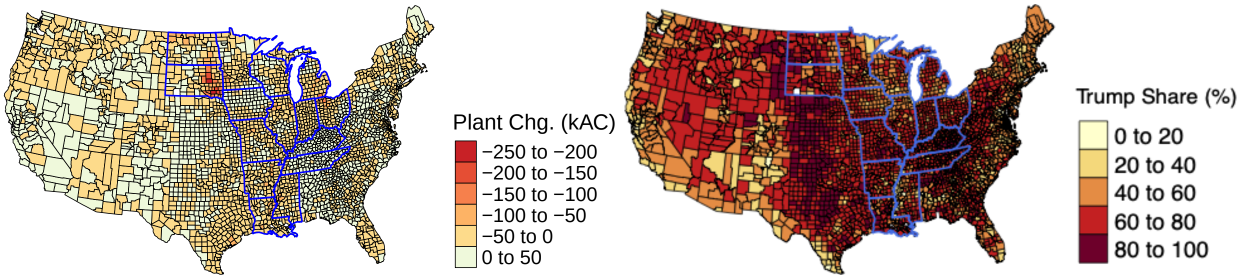
[5]For a full list of agricultural products that we include to construct our measure, see Appendix D. This list is based on the Ministry of Commerce of China, "Announcement on the imposition of tariffs on certain products originating in the United States", 2018 No. 55, June 16, 2018 (http://www.mofcom.gov.cn/article/ae/ai/201806/20180602756389.shtml).

[6]For details of the matching procedure, see Appendix E.

[7]We calculated the difference in the *planted* area between 2018 and 2019, rather than the difference in the *harvested* area. A farmer's choice of a crop mix - which crops to plant on which fields - and planting volume is made in the pre-planting season (between January and mid-March) for a given crop year. Thus, the planted volume in Spring 2019 rather than the harvested volume in Fall 2019 better reflects farmers' immediate responses to tariffs imposed in the previous year.

[8]For a more detailed image of the soybean belt, see Appendix C.

[9]Data from the CQ Voting and Elections Collection (CQ Press, 2020). Because the Cropland Data Layers does not provide annual planting estimates for Alaska and Hawaii regions, we exclude election results from both states as well.



(a) Changes in Tariffed Crop Planting (kAC) (b) Trump Vote Share (%)

Figure 2. Geographical Distributions of Support for Donald Trump and the 2018-2019 Changes in Tariffed Crop Planting. This figure displays county-level variation in Trump support (%) and changes in tariffed crop planting (kilo acres). Panel (a) presents county-level changes in tariffed crop planting between 2018 and 2019. Panel (b) presents county-level distribution of Trump's vote share in the 2016 Presidential election. In Panel (a), moving from lighter red to darker red indicates increase in tariffed crop planting (in kilo acres). In Panel (b), darker red indicates higher vote shares for Trump in 2016. Blue border lines indicate top 15 soybean-producing states.

nomic accounts database.[10] We adjust for county size and the importance of the agricultural industry with (logged) `population`, `share of planting land` (% of land used for agricultural production), `change in agricultural share` (% change in agricultural industry's share of economy), and the amount of land previously reserved for environmental protection using data from the the Conservation Reserve Program (`CRP`),[11] `share of individual farms` compared to corporate farms in the industry, `share of agricultural employment` (% of jobs from agriculture), `number of farms`, and total `wages` given to their workers. Additionally, we consider the role of crop diversification (Aguilar et al. 2015; Roesch-McNally, Arbuckle and Tyndall 2018). When the demand for one of the planted crops is expected to decline in the forthcoming year, a farmer can switch to alternative crops to minimize the loss. `Rotatable` is a binary indicator where one means a crop that takes the majority of the total production is not subject to Chinese tariffs, while zero means the majority of the production is subject to Chinese tariffs.

We also adjust for farmers' characteristics aggregated at the county level such as farms'

[10] https://www.bea.gov/data/economic-accounts/regional.

[11] The Conservation Reserve Program (CRP), administered by the USDA Farm Service Agency, sets a minimum area of land to be reserved for environmental health and quality purposes. When these grants end, as many did in 2019, farmers are more likely to increase planting. For details, see https://www.fsa.usda.gov/programs-and-services/conservation-programs/conservation-reserve-program/.

net income, government payment to the agricultural industries, and, crucially, trade-war specific subsidies, through the Market Facilitation Program (MFP). In addition, we use the USDA's 2017 Agricultural Census data (USDA-NASS, 2017) to collect average farm size (thousand acres), average structure of farm ownership (% of land in farms operated based on full ownership), and average percentage of white farmers (% farms with white producers) in each county. County-level education attainment is also adjusted using the percentage of the adult population with at least a high school degree (High School) and percentage of the adult population with at least a bachelor's degree (College) based on the American Community Survey estimates.

Lastly, weather conditions play a large role in agricultural production, which was particularly the case in 2018. Record flooding delayed planting in much of the soybean belt and the Midwest. Therefore, we measure average daily precipitation and temperature levels to determine the predicted success of crop yields, which informs planting decisions. We follow Huang and Moore (2019) and include average daily *temperature* (°C) and *precipitation* (millimeters) in the pre-planting season (January 1 to March 14) using Wolfram Schlenker's *Daily Weather Data for Contiguous United States* (Schlenker, 2020). This dataset contains daily precipitation levels and minimum/maximum temperature for each predefined *grid* covering the entire US territory, which are then aggregated at the county level. We rely on Schlenker's own algorithm to compute average daily temperature and precipitation levels given temperature bounds in the data.[12]

Table 1 presents the summary statistics of our data.[13]

[12]Note that successful annual crop yield is determined by whether the planting season (March - May) has a good number of days that fall into optimal minimum and maximum temperature/precipitation bounds defined for each crop. Farmers typically rely on average temperature and precipitation levels in the *pre-planting* season (January - March) to select a mix of crops and planting volumes for each of the crops they choose. The resulting measures included in our models are based on optimal temperature/precipitation bounds for *soybean*, a crop that is central to our analysis.

[13]Appendix F provides correlations among these variables: Trump's vote share, changes in crop planting, key local level variables from the US Bureau of Economic Analysis (BEA), American Community Survey, the US Department of Agriculture's 2017 Agricultural Census, and weather data.

Statistic	N	Min	Q_1	Med	Mean	Q_3	Max	St. Dev.
Trump Share (%)	3,106	4.1	54.6	66.4	63.3	74.9	94.6	15.6
ΔTariffed Planting (acre)	3,108	-229.1	-3.6	-0.1	-4.8	0.4	47.2	17.0
ΔTariffed Planting (%)	3,107	-85.9	-2.6	-0.4	-1.0	1.2	70.5	6.9
ΔSoy Planting (acre)	3,108	-147.5	-4.4	-0.2	-4.7	0	19.9	12.2
ΔSoy Planting (%)	3,107	-57.9	-4.1	-0.7	-2.4	0	50	5.7
(log) Population	3,055	5.1	9.3	10.2	10.3	11.1	16.1	1.5
High School (%)	3,108	7.3	29.7	34.5	34.2	39.1	57.4	7.2
College (%)	3,108	0.0	10.1	13.2	14.2	17.3	45.4	5.7
Planting Land (%)	3,108	0	3.8	16.1	27.2	47.5	93.1	27.3
ΔAgri-share (%)	2,724	-35.8	-0.5	0	0	0.5	47.9	4.1
Tariffed Employment	3,055	0	0	0	63.2	8.0	15,625.0	540.0
Soy Employment	3,108	0	0	0	0.5	0	151.0	4.8
Tariffed Wage	3,108	0	0	0	2,212.51	228.13	633,393.27	18,960
Soy Wage	3108	0	0	0	16.68	0	5,244.96	156.74
Tariffed Farms	3,108	0	0	2	8.7	7	842	30
Soy Farms	3,108	0	0	0	0.4	0	31	1.3
Farm Income	3,055	-70,253	-933.5	5,304	20,878.6	1,985,623	84,154	22,518
Gov. Payments	3,055	0	654	2,846	7,107.8	10,836.5	75,545	9,354.4
MFP	3,108	0	0.4	2.3	5.7	8.1	220.9	9.3
CRP (%)	3,104	0	0	0	0.3	0.2	27.1	1.1
Avg. Farm Size	3,055	0	0.2	0.3	0.7	0.5	58.5	1.7
Avg. Ownership (%)	2,927	0	22.9	38.4	39.2	53	100	19.1
Tariffed Rotatable	3,108	0.0	1.0	1.0	0.8	1.0	1.0	0.4
Soy Rotatable	3,108	0.0	1.0	1.0	0.9	1.0	1.0	0.3
Avg. White (%)	3,068	0	96.8	99.1	96.5	99.8	100	7.7
Avg. Precipitation	3,035	11.6	106.9	185.5	203.2	264.4	777.5	126.2
Avg. Temperature	3,035	-17.4	-4.4	1.7	1.4	7.5	21	7.7

Table 1. Summary Statistics.

5 Empirical Findings

The empirical findings support our hypothesis. We hypothesized that farmers in Trump-supporting counties should be less likely than other farmers to decrease their production of tariffed goods in response to the tariff shock from China. We test this relationship in two parts. First, we run a set of OLS regression models on cross-sectional data to see whether different political districts made different planting decisions in response to the tariff shock between 2018 and 2019. Second, we measure the differential responses to the 2018 Chinese tariff shock through a panel difference-in-differences approach. We find that counties with varying levels of Trump partisanship responded differently to the tariffs. An increase in Trump partisanship decreases a county's likelihood of responding to the 2018 tariffs by moving away from tariffed crops.

5.1 Cross-sectional Models

In our first models we test the relationship between partisanship and farmers' crop planting practices in 2018 and 2019 using the following specification.

$$Y_i = \alpha + \beta X_i + \gamma^\top \boldsymbol{Z_i} + \delta_s + \epsilon_i, \text{ where}$$

the main outcome variable of interest, Y_i is `change in tariffed crop planting` between 2018 and 2019 measured in thousand acres. X_i is `Trump's vote share` in the 2016 presidential election. Both of these variables vary at the county level.

Next, $\boldsymbol{Z_i}$ constitutes a vector of county-level characteristics that we adjust for confounding, as described in the previous section. This includes `share of planting land`, `change in agriculture's share in economy`, land reserved for environmental protection (Conservation Reserve Program, `CRP`), (logged) `population`, educational attainment (`High School` and `College`), `net income` of farms, `share of agricultural employment`, `share of individual farms` compared to corporate farms, `government payment` to agricultural industries, trade war specific subsidies (Market Facilitation Program, `MFP`), `employment from tariffed industries`, `total wage` from tariffed industries, `number of tariffed farms`, average `farm size`, average `farm ownership`, county-level availability to rotate to non-tariffed crops (`rotatable`), average ratio of `white` farmers, average daily `precipitation` and `temperature` levels. We also add state fixed effects.

The primary quantity of interest is β, which we expect to be positive and statistically significant. This would indicate that counties that support president Trump more, on average, will *increase* their planting of crops that were targeted by the 2018 Chinese tariffs. Conversely, counties that showed lower support for Trump in the 2016 presidential election are more likely to *decrease* their planting of tariffed goods after the tariffs were announced.

We also test the robustness of our hypothesis by running the same model using only soybean data, and soybean data within the soybean belt states, rather than aggregating all tariffed goods. Soybeans are one of the most heavily affected crops during the trade war due to the fact that 60% of US soybean exports before the trade war went to China (Hart and Schulz, 2015). Therefore, if anything, we expect β to be larger when we isolate the effect on soybeans. We run these models using ordinary least-squares and using several subsets of the data.

Table 2 presents the main findings from the OLS regression models. Models 1 and 2 show the baseline OLS results on the effect of partisanship on crop planting changes of all tariffed crops. In Model 2, standard errors are clustered at the state level. Consistent with our expectation, the correlation is positive and statistically significant across models. In Model 3, we run a multi-level OLS regression with counties nested within states.

Models 4 and 5 display more specific results, isolating soybean planting as the outcome measure. Here we use the number of farms, employees, and the total wages paid to workers from these farms, instead of those from the entire agricultural industries that were affected by the tariffs. Model 5 uses only the observations from 15 *soybean belt* states.[14]

[14]Soybean production in the United States is concentrated mainly in upper Midwest and near Mississippi river that typically include Arkansas, Iowa, Illinois, Indiana, Kentucky, Louisiana, Michigan, Minnesota,

	Dependent Variable:				
	Δ Tariffed Acres			Δ Soy Acres	
	(1)	(2)	(3)	(4)	(5)
Trump Share (%)	0.131***	0.131***	0.123***	0.102***	0.270***
	(0.028)	(0.026)	(0.028)	(0.019)	(0.044)
Planting Land (%)	0.213***	0.213***	0.212***	0.139***	0.287***
	(0.024)	(0.037)	(0.024)	(0.016)	(0.032)
ΔAgri-share (%)	−0.693***	−0.693***	−0.681***	−0.291***	−0.385***
	(0.067)	(0.150)	(0.067)	(0.044)	(0.078)
Rotatable	2.018**	2.018**	1.961**		
	(0.856)	(0.926)	(0.851)		
Rotatable (Soy)				3.330***	3.425***
				(0.772)	(1.094)
High School (%)	−0.008	−0.008	−0.015	0.003	0.348***
	(0.084)	(0.079)	(0.082)	(0.054)	(0.117)
College (%)	0.074	0.074	0.065	0.029	0.383***
	(0.101)	(0.095)	(0.100)	(0.066)	(0.141)
Gov. Payments	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.00004)	(0.0001)
MFP	0.257***	0.257***	0.255***	0.047	−0.082
	(0.077)	(0.082)	(0.076)	(0.039)	(0.122)
Farm Size	1.501***	1.501***	1.464***	0.832***	8.1555***
	(0.323)	(0.466)	(0.320)	(0.210)	(1.045)
Ownership (%)	0.237***	0.237***	0.238***	0.131***	0.350***
	(0.024)	(0.025)	(0.024)	(0.016)	(0.037)
White (%)	−0.129**	−0.129***	−0.115**	−0.073**	−0.270***
	(0.056)	(0.049)	(0.056)	(0.037)	(0.100)
Precip.	−0.009**	−0.009**	−0.008*	−0.009***	0.006
	(0.004)	(0.003)	(0.004)	(0.003)	(0.007)
Temperature	0.213	0.213*	0.236**	0.244***	0.013
	(0.136)	(0.125)	(0.114)	(0.088)	(0.196)
Model	OLS	OLS	Mixed	OLS	OLS
Sample	Full	Full	Full	Full	SoyBelt
N	2,554	2,554	2,554	2,554	1,108
State FE	✓	✓		✓	✓
F-Stats	29.68			45.48	50.41
Log Likelihood			−10,408.25		
AIC			20,864.51		
BIC			21,004.80		

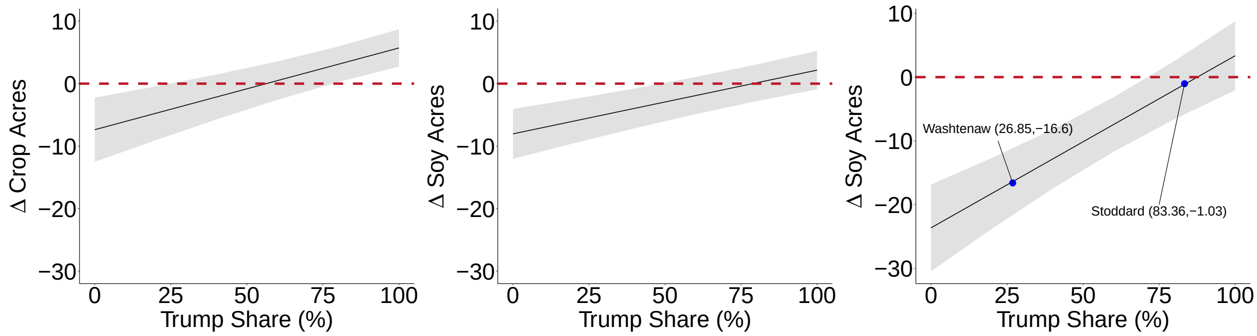
*p<0.05; **p<0.01; ***p<0.005.

Table 2. Partisan Optimism on Tariff-affected Production. This table presents the OLS estimates of the effects of partisanship optimism on changes in tariffed crop planting. All regressions except Model 3 have state fixed effects. In Model 2, standard errors are clustered at state level. Full results are available in Table G1.

The results suggest that Trump vote-share influenced the overall planting of crops that were hurt by Chinese retaliatory tariffs in the year following tariff imposition. The estimates reported in the first row of Models 1, 2, and 3 show that a one-percentage point increase in Trump's vote share in the 2016 presidential election translates to about 123 to 131-acre increase in planting of crops affected by Chinese tariffs. Therefore, a one-standard-deviation increase in Trump vote-share (15%) could increase planting of tariff-affected crops by up to 1,800-2,000 acres. The median county in our data contains 55,500 acres of total farmland, so this change in political preferences could shape around three percent of overall farmland. The substantive effects become larger in the soybean-specific models. Model 4 shows a one-percent increase in Trump vote share translating into an increase of 102 soybean acres. This increases even further in Model 5, to 270 soybean acres in the 15 soybean-belt states.[15]

Mississippi, Missouri, North Dakota, Ohio, South Dakota, Tennessee, and Wisconsin, although the number of states differ across sources. See https://farmdocdaily.illinois.edu/2013/07/concentration-corn-soybean-production.html.

[15]In Appendix H, we run a set of spatial econometrics models to further adjust for potential spatial dependence across counties.



(a) Tariffed Crops in US States (b) Soybean in US States (c) Soybean in Soy Belt

Figure 3. Predicted Changes in Crop Acres by Trump Vote Share. This figure presents predicted changes and confidence intervals with 95% of confidence in crop planting volumes by Trump vote share. Each panel is based on results from Columns 2, 4, and 5 in Table 2.

Figure 3 further displays the substantive implications of the results. Panels in Figure 3 present the point estimates and the surrounding confidence intervals with 95% of confidence of the predicted changes in crop planting volumes by Trump vote share. These results show that the effect of Trump support on crop planting could be substantively large. For example, based on results from Panel (c), counties in the Soybean belt that exhibit extreme support for Trump, such as Stoddard, Missouri (83.36%), were likely to plant about 15,000 acres of soybean more than their Democratic counterparts, such as Washtenaw, Michigan (26.85%) during the trade war. Given that the average US soy planting in 2019 was around 49,000 acres, and 25,000 acres in Soybean belt states respectively, the 15,000-acre difference between extreme Republican counties and Democrats is quite substantial.

Apart from the direct results regarding Trump vote-share, the models provide interesting findings in some of the control variables as well. In all full-sample models, larger farms translated into more responsiveness to the trade war. This could be because larger farms have more resources to endure the overall damage introduced by the tariffs, so are more likely to maintain the previous planting trends compared to farms that are small. On average, a one-thousand acre increase in the size of farms translates to around 1,500-acre increase in planting of tariffed crops. Similarly, counties with independently owned farms were more likely to increase planting of tariffed goods. This may seem puzzling, as independent owners might be expected to be more able to change their farming practices. However, this itself may be a reflection of political factors. Farms with independent owners may be more likely to respond to political incentives. In future research, it would be interesting to interact political preferences with the independent ownership measure. Also, contrary to the finding that farms with more government subsidies were also likely to decrease tariffed goods, trade-war specific subsidies (Market Facilitation Program) to farms was positively associated with an increase in tariffed crop planting.

5.2 Panel Models

To gauge the robustness of our previous findings, we run another set of models considering the *interaction* between partisanship and the 2018 Chinese tariff shock. In an approach similar to a panel difference-in-difference design, we consider the differential reactions to the tariff shock for counties with different Trump vote-shares. The dependent variable in these models is the *count* of areas of tariffed crops planted in a county.[16] We add a binary indicator representing the tariff shock, coded as 0 in 2018 and before the trade war and 1 from 2019 onward, during the trade war. To calculate the politicized differences in planting behavior, we interact the tariff shock variable with a measure of Trump vote share. The estimating equation is as follows, with i indexing counties and t years.

$$\begin{aligned}\text{Tariffed Planting}_{i,t} &= \beta_1 + \beta_2 \text{Trump Share}_i + \beta_3 \text{Tariff}_t \\ &\quad + \beta_4 \text{Tariff}_t \times \text{Trump Share}_i + \beta^\top \text{Controls}_{i,t} + \gamma_t + \delta_i + \epsilon_{i,t}\end{aligned}$$

In these models, we are interested in two coefficients. First, β_3 represents the reaction to the tariff shock for a hypothetical county in which nobody supported Trump. We expect this coefficient to be negative and significant: counties with very low support for Trump should not be likely to follow his instructions and continue planting tariffed crops after 2018. β_4,

[16] Each area corresponds to a pixel in the USDA crop layer satellite imagery data, which approximately equals 22.2 acres. The dependent variable is the total count of these pixels in a given county.

the interaction coefficient of `Trump Share` × `Tariff`, represents the change in crop planting behavior as a county's support for President Trump increases. We expect this coefficient to be positive and significant: a higher Trump vote-share should inspire farmers to ignore the negative effects of the tariffs. We include the same battery of control variables as in the previous section, many of which vary over time as well as cross-sectionally. Due to the count nature of the dependent variable, we estimate a poisson model.

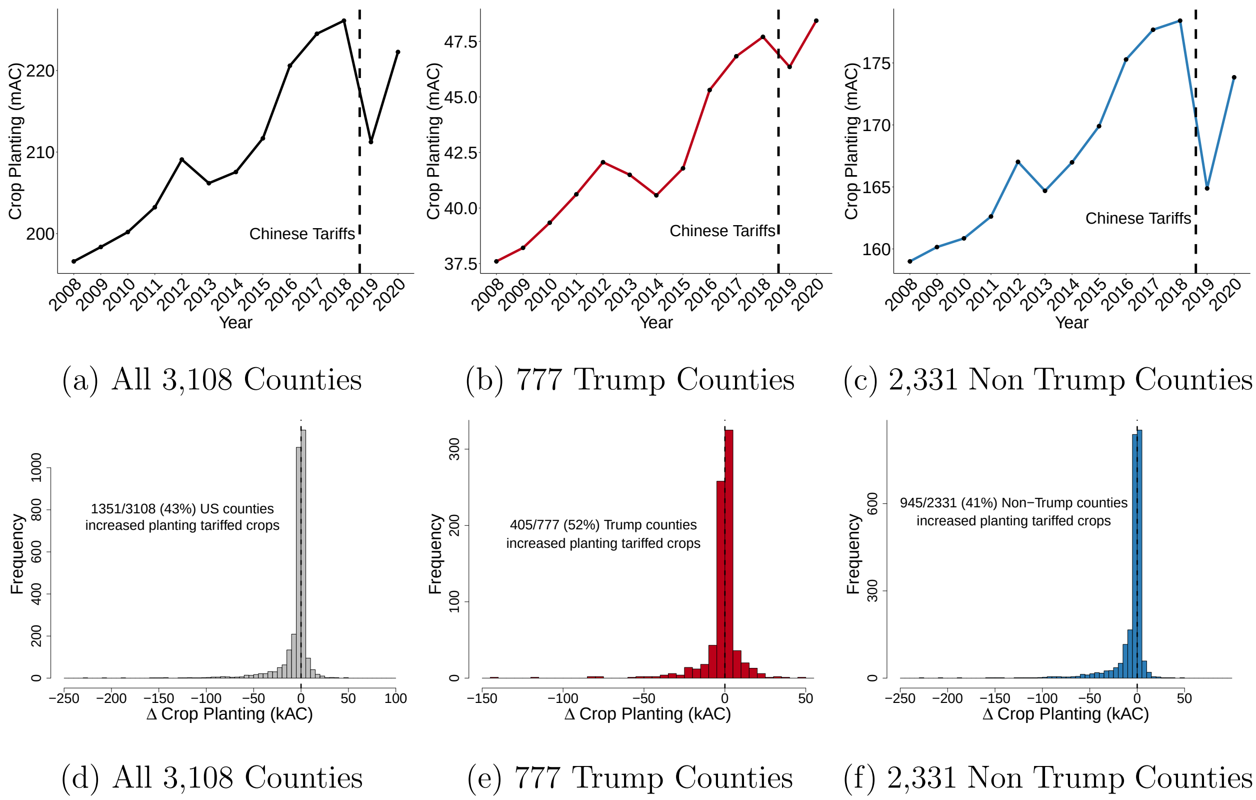
As shown in Table 3, all models show the expected relationships for β_3 and β_4. Counties with a low Trump vote-share responded to the tariff shock by decreasing their reliance on tariffed goods. However, as Trump vote-share increased, counties became more likely to continue planting those goods. These trends are consistent with the estimates in previous models. Also, like the previous models, the soybean-specific coefficients are higher than the ones including all tariffed goods.

	Dependent Variable:				
	Δ Tariffed Count				Δ Soy Count
	(1)	(2)	(3)	(4)	(5)
Trump Share (%)	0.003***	−0.299***	−0.005***	−0.073***	−0.196***
	(0.00000)	(0.001)	(0.00000)	(0.001)	(0.001)
Tariff	−0.119***	−0.005***	−0.230***	−0.115***	−0.041***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0004)
Trump Share× Tariff	0.006***	0.001***	0.002***	0.002***	0.002***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)
N	15,530	15,530	10,338	10,338	15,530
Controls	✗	✗	✓	✓	✗
County FE	✗	✓	✗	✓	✓
Year FE	✗	✓	✗	✓	✓
Log Likelihood	−4,051,338,361	−22,833,012	−493,933,592	−8,473,181	−13,932,779
AIC	8,102,676,730	45,672,247	987,867,231	16,952,278	27,871,782

*p<0.05; **p<0.01; ***p<0.005.

Table 3. Partisan Optimism on Count of Tariff-affected Areas. This table presents estimates from poisson maximum likelihood models. Full results are available in Table G2. Models 2, 4, and 6 have county and year fixed effects.

Looking back at the original puzzle introduced in Figure 1, a disaggregation of political



(a) All 3,108 Counties (b) 777 Trump Counties (c) 2,331 Non Trump Counties

(d) All 3,108 Counties (e) 777 Trump Counties (f) 2,331 Non Trump Counties

Figure 4. Trends in Tariffed Crop Planting (2008-2020) and Changes in Tariffed Planting in 2019. This figure presents trends in tariffed crop planting (million acres) in 2008-2020 and changes in tariffed planting (thousand acres) in 2019 by Trump's vote share. Panels (a) to (c) indicate the 2008-2020 trends, and (d) to (f) indicate the changes in tariffed acres in 2020. Panel (a) and (d) report the trend and changes in all 3,108 US counties. Panel (b) and (e) present the same for Trump counties that had above 3 quartile (74.9%) vote share in the 2016 presidential election. Panel (c) and (f) indicate results for non-Trump counties that had below 3 quartile vote share.

districts provides further illumination. Figure 4 breaks down the same data by political preferences of the district. Panel (a) shows the overall effect of the tariffs: planting of tariffed goods sharply decreased overall. However, Panel (b) limits the data to the most extreme Trump-supporting counties, or counties whose 2016 Trump vote-share fell into the top 25^{th} percentile. These counties exhibit a much lower, if any, drop in planting of tariffed goods. Only around half of these counties decreased their planting of these goods. Finally, Panel (c) shows that the overall effect of the tariffs was much stronger in non-Trump counties (counties whose vote-share fell in the bottom 75^{th} percentile). Only 41% of these counties increased their total planting levels. Most of the puzzling overall results were felt in counties with the most extreme political preferences. This is in keeping with our model of partisan motivations for trade preferences.

6 Conclusion

The empirical findings support the hypothesis that political preferences can partially explain the response to the US-China Trade War. Although this paper discusses only one specific industry—agriculture—it should be relevant to other types of producers as well. Farms were certainly not the only businesses affected by the recent trade war. China issued tariffs on other imports, such as automobiles, as part of their retaliation, and the initial steel and aluminum tariffs imposed by the US government also strained many US companies (Morris, 2020). Therefore, given the right data, it should be possible to find evidence for these same mechanisms in a variety of sectors.

In fact, if anything, the agricultural industry creates a hard test for the theory. The local signaling mechanism is weak in the agricultural sector, where businesses often rely upon migrant labor and rarely compete in the local labor market. Similarly, farmers' clientele is often less local than the type of businesses that open local store-fronts. Relatively low local competition for both labor and customers decrease the incentives for firms to behave ideologically. Also, large farms often find it difficult to quickly switch crops, often preferring to plan planting activities well in advance. For these reasons, it is likely other types of business would be more, not less, responsive to political pressures than the agricultural sector.

These mechanisms should also be relevant to a wider variety of trade policies than the 2018 US-China Trade War. This event was an extremely straightforward example of a partisan leader tying his reputation to a specific product. But it was also very clear from the start that farmers would face at least some short-term losses. The 2018 trade war was a relatively high-information context, and previous work on trade preferences suggests that information is one of the greatest barriers blocking individuals from following their pocketbook (Rho and Tomz 2017). Heuristics are more important when it is more difficult to gather accurate information. Therefore, if these findings hold in very high-information contexts, then they may also hold in cases where the effects of trade are only visible "through a glass and darkly" (Hiscox 2006). On the other hand, it is possible that business leaders rarely face information constraints the way the public does. The level of applicability of this theory to other trade policies is an area for future research.

Another area for future research is the role of the so-called "China Shock" of the early 2000s on farmers' preferences. Some electoral districts were affected more than others when China acceded to the WTO and entered global trade (Autor, Dorn and Hanson, 2013). This has had clear political implications (Autor et al., 2020). In future research, it will be interesting to test the role of local trade shocks on county-level responses to the trade war. It is possible that many of the communities that followed Trump's advice already bore economic scars from trade with China. The extent to which their behavior is a result of previous policies will be important to determine.

This paper makes contributions towards answering two lingering questions in the trade literature. First, much literature has noted that trade preferences often do not appear to follow from rational self-interest. While some literature argues that this is due to ignorance of trade policy (Hiscox 2006; Bearce and Tuxhorn 2017; Rho and Tomz 2017), our results suggest that ideological and social factors can also play a role (Guisinger 2017; Mansfield and Mutz 2009). In contrast to much of the existing literature on trade attitudes, which relies on survey responses, our behavioral measure of trade preferences negates arguments that non-rational trade preferences are just cheap talk. We also build on a new and promising literature that considers firms as independent actors in international relations. Following Melitz (2003)'s new-new trade theory that highlighted the role of firm heterogeneity, scholars have been scrambling to access and evaluate firm-level trade behavior data (Kim and Osgood, 2019). Although this project does not contain firm-level data, it nevertheless provides valuable insights on firms' responses to the trade war.

This research suggests a series of policy considerations. First, contrary to many economic models, policymakers cannot always rely on business owners to support policies that are good for their bottom line. Partisan affinity plays a role in determining production, often to the detriment of the producer, and the economy as a whole. This suggests that business-minded policymakers and trade associations need to work harder to provide accurate information about the costs and benefits of policies. The existing literature suggests that increased information decreases motivated reasoning (Hill, 2017). This may provide a crucial path forward for policymakers and others who wish to ensure a smoothly functioning economy. Affective polarization doesn't just affect individuals; it can amplify itself in firm behavior as well.

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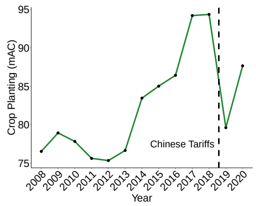
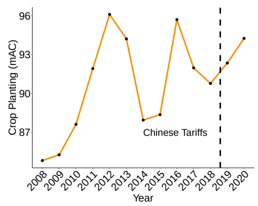
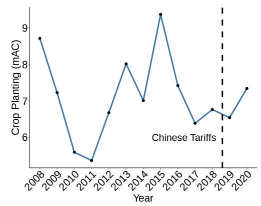
Appendix A. Trends in US Crop Planting, 2008-2020



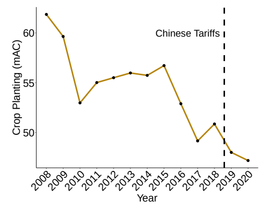
(a) Soy Volume



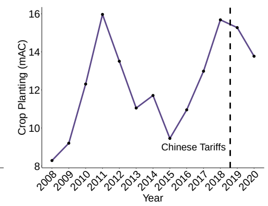
(b) Corn Volume



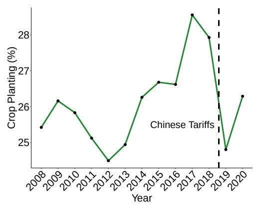
(c) Sorghum Volume



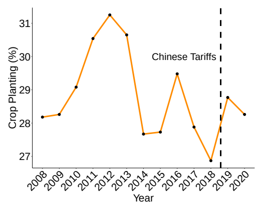
(d) Wheat Volume



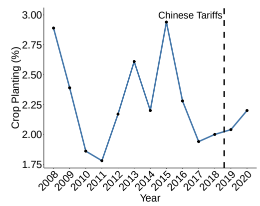
(e) Cotton Volume



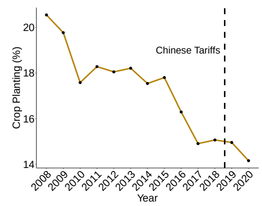
(f) Soy Ratio



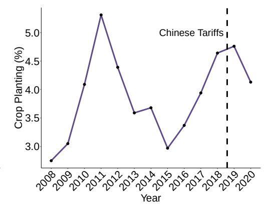
(g) Corn Ratio



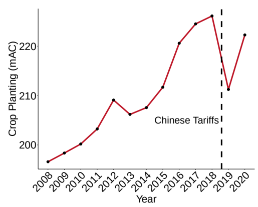
(h) Sorghum Ratio



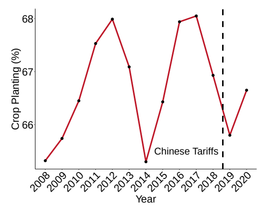
(i) Wheat Ratio



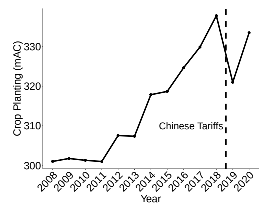
(j) Cotton Ratio



(k) Tariffed Volume



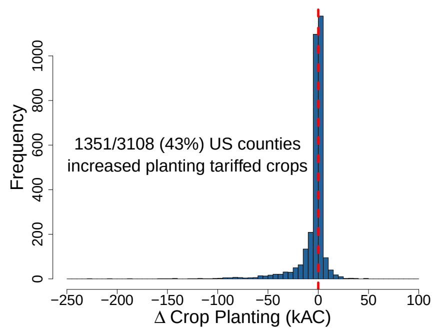
(l) Tariffed Ratio



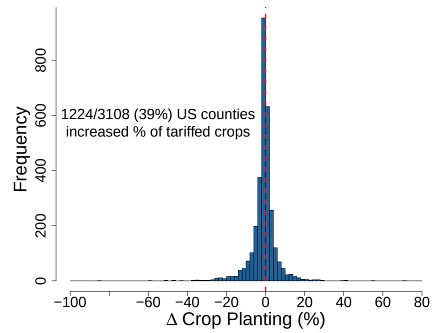
(m) Total Volume

Figure A. Trends in US Crop Planting by Crop Type, 2008-2020. This figure shows trends in crop planting in the United States by crop types between 2008 and 2020. Data from USDA's Cropland Data Layer, Alaska and Hawaii excluded. Panels (a) through (e) and Panel (k), (m) correspond to trends in crop planting volume in million acres. Panels (f) through (j) and Panel (l) indicate trends in crop planting ratio for each crop type. Dashed lines indicate Chinese tariffs imposed on July 6, 2018.

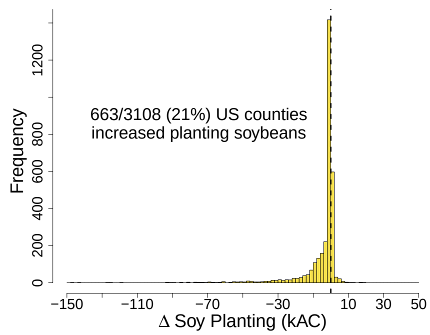
Appendix B. Variation in Planting Changes by County



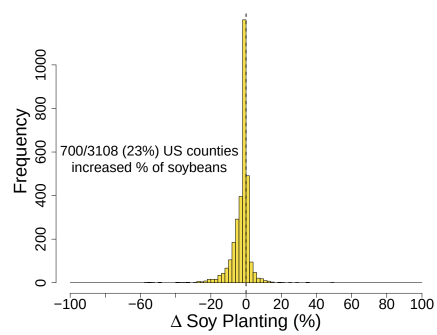
(a) Change in Tariffed Volume



(b) Change in Tariffed Ratio



(c) Change in Soy Volume



(d) Change in Soy Ratio

Figure B. Variation of Planting Changes in US Counties, 2019. This figure displays variation in planting changes by US counties in 2019. Data is drawn from the US Department of Agriculture's CropScape Crop Data Layers. Alaska and Hawaii regions are excluded. Panels (a) and (c) each shows that 43% and 21% of US counties planted more tariffed crops and soybeans in 2019. Panels (b) and (d) show that 39% and 23% of US counties have switched their production portfolio towards planting more tariffed crops and soybean in 2019, measured as $\frac{\text{2019 tariffed crop}}{\text{2019 total crop}} - \frac{\text{2018 tariffed crop}}{\text{2018 total crop}}$ and $\frac{\text{2019 soybean}}{\text{2019 total crop}} - \frac{\text{2018 soybean}}{\text{2018 total crop}}$, respectively.

Appendix C. Geographical Distributions

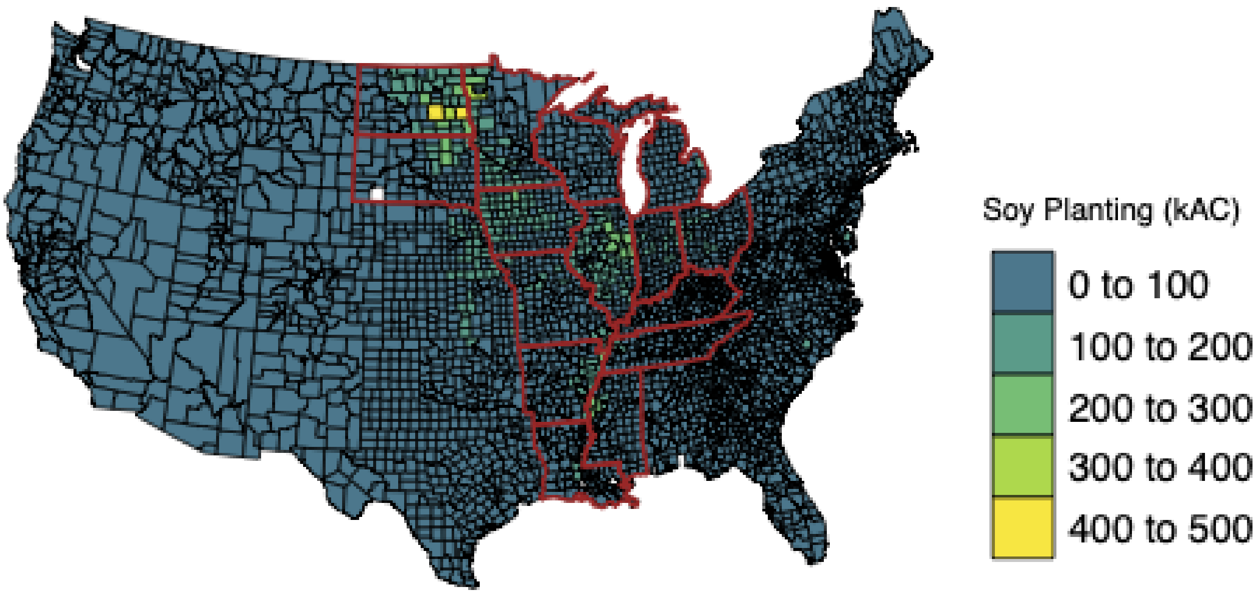


Figure C1. US Soybean Planting by Acres in 2019. This figure presents the geographical distribution of soybean planting by acres in the United States, 2019. Red borderlines indicate 15 US states that constitute the *Soybean Belt*: Arkansas, Iowa, Illinois, Indiana, Kentucky, Louisiana, Michigan, Minnesota, Mississippi, Missouri, North Dakota, Ohio, South Dakota, Tennessee, and Wisconsin. White cells indicate missing data.

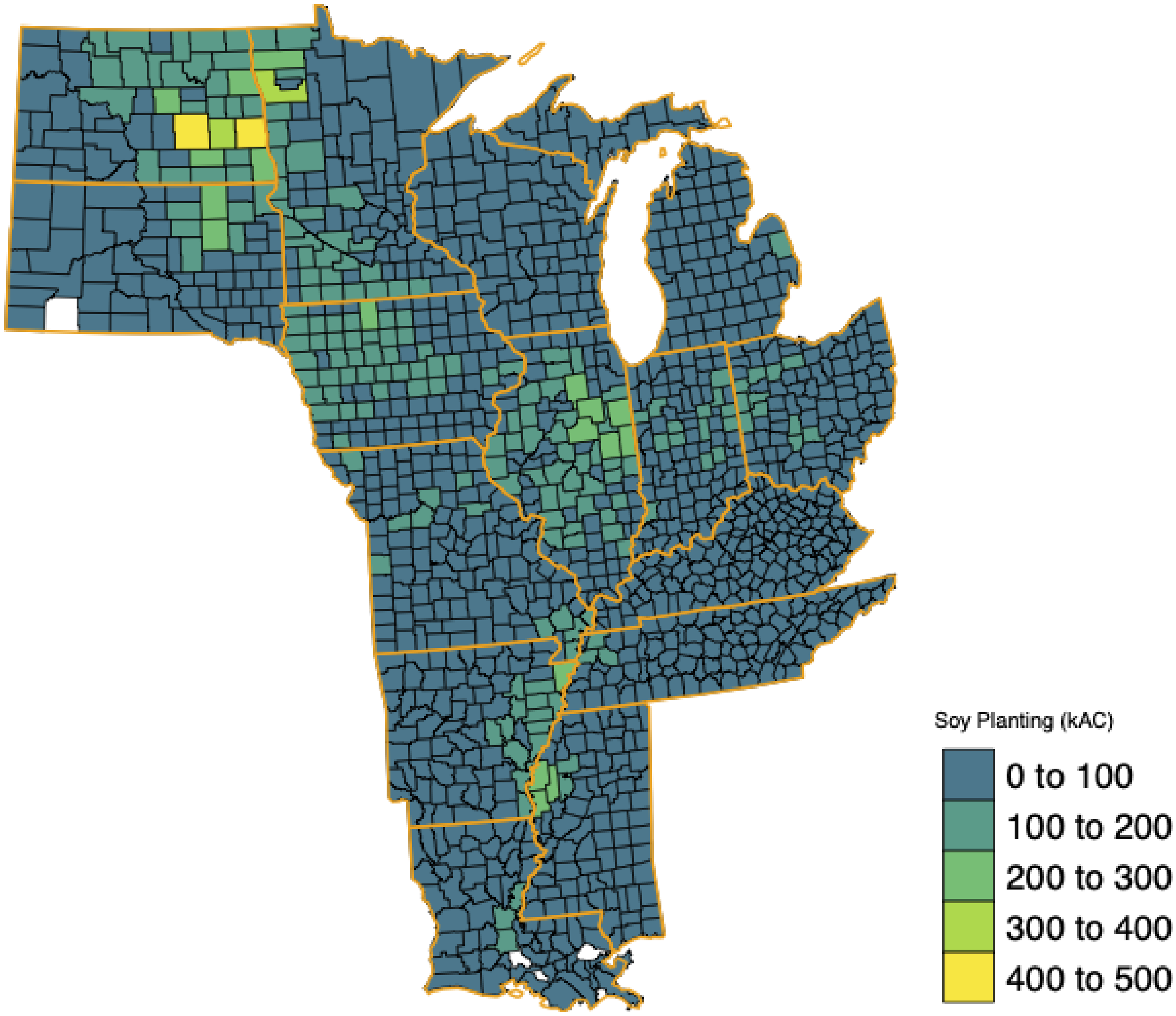
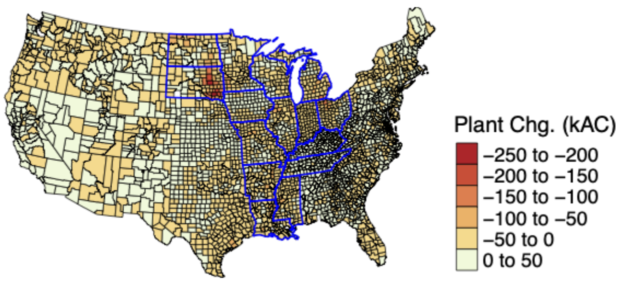
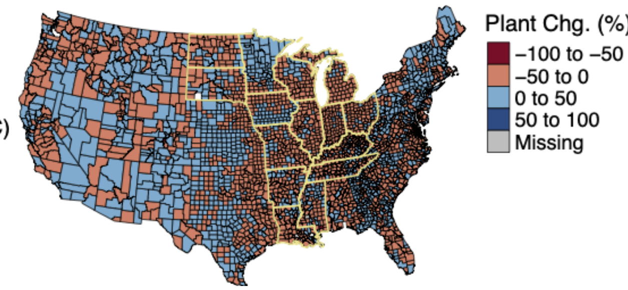


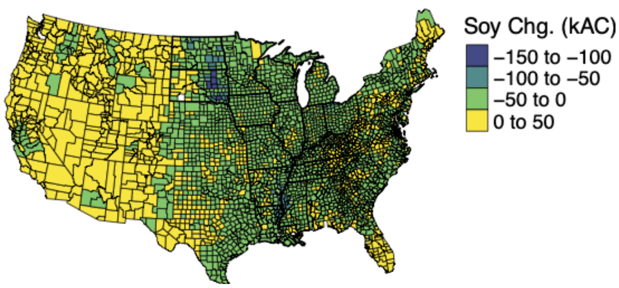
Figure C2. Soybean Planting by Acres in the Soybean Belt, 2019. This figure highlights the geographical distribution of soybean planting by acres in the US Soybean belt states, 2019. Soybean belt states are Arkansas, Iowa, Illinois, Indiana, Kentucky, Louisiana, Michigan, Minnesota, Mississippi, Missouri, North Dakota, Ohio, South Dakota, Tennessee, and Wisconsin. White cells indicate missing data.



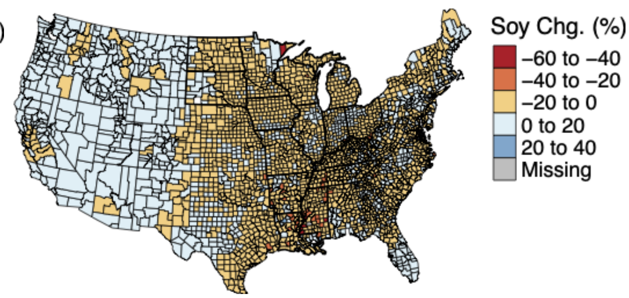
(a) Changes in Tariffed Crop Planting (kAC)



(b) Changes in Tariffed Crop Planting (%)



(c) Changes in Soybean Planting (kAC)



(d) Changes in Soybean Planting (%)

Figure C3. Changes in Crop Planting. This figure describe county-level variation in changes in crop planting between 2018 and 2019. Borderlines indicate 15 US states that constitute the *Soybean Belt*: Arkansas, Iowa, Illinois, Indiana, Kentucky, Louisiana, Michigan, Minnesota, Mississippi, Missouri, North Dakota, Ohio, South Dakota, Tennessee, and Wisconsin.

Appendix D. List of US Agricultural Products Subject to Chinese Tariffs Matched with USDA Classification

HTS Code	Tariff-affected Item Name	CropScape Type
3036500	Frozen green barley	Barley
3047300	Frozen green barley fillet	Barley
7011000	Potatoes	Potatoes
7019000	Fresh or frozen potatoes	Potatoes
7020000	Fresh or refrigerated tomatoes	Tomatoes
7031010	Fresh or refrigerated onions	Onions
7032010	Fresh or refrigerated garlic head	Garlic
7032020	Fresh or refrigerated garlic and seedlings (stew garlic)	Garlic
7032090	Other fresh or refrigerated garlic	Garlic
7039020	Fresh or refrigerated green onions	Onions
7041000	Fresh or chilled cauliflower and Cabbage	Cabbage
7049010	Fresh or refrigerated cabbage	Cabbage, Cauliflower
7049020	Fresh or refrigerated broccoli	Broccoli
7049090	Fresh or cold other food mustard	Mustard
7051900	Fresh or refrigerated other lettuce	Lettuce
7061000	Fresh or refrigerated carrots	Carrots
7069000	Fresh or refrigerated radishes and similar edible rhizomes	Radishes
7070000	Fresh or refrigerated cucumbers	Cucumbers
7081000	Fresh or refrigerated peas	Peas
7092000	Fresh or refrigerated asparagus	Asparagus
7093000	Fresh or refrigerated eggplant	Eggplants
7094000	Fresh or refrigerated celery	Celery
7096000	Fresh or refrigerated pepper	Peppers
7099200	Fresh or refrigerated olives	Olives
7099300	Fresh or refrigerated pumpkin	Pumpkins
7122000	Dried onion	Onions
7129050	Dried garlic	Garlic
7131010	Dry peas	Peas
7131090	Dry peas	Peas
7132090	Dried chickpeas	Chickpeas
7134010	Dried lentils	Lentils

7134090	Dried lentils	Lentils
7135010	Dry beans	Dry Beans
7135090	Dried broad beans	Dry Beans
7136010	Dried beans	Dry Beans
7136090	Dry bean	Dry Beans
7142011	Fresh sweet potatoes	Sweet Potatoes
7142019	Fresh sweet potato	Sweet Potatoes
7142020	Dried sweet potato	Sweet Potatoes
8021100	Fresh or dry almond kernels	Almonds
8021200	Fresh or dried almonds	Almonds
8023100	Fresh or dried unshelled walnuts	Walnuts
8023200	Fresh or dried shelled walnuts	Walnuts
8025100	Fresh or dried unhulled pistachio fruit	Pistachios
8025200	Fresh or dried hulled pistachio fruit	Pistachios
8051000	Fresh or dried orange	Oranges
8052190	Fresh or dried other citrus	Oranges, Citrus
8052200	Fresh or dried Clementine orange	Oranges
8052900	Other fresh or dried Welkin orange and hybrid citrus	Citrus
8059000	Other fresh or dried citrus fruits	Citrus
8061000	Fresh grapes	Grapes
8071100	Fresh watermelon	Watermelons
8071910	Fresh cantaloupe	Cantaloupes
8081000	Fresh apples	Apples
8083010	Fresh pear snow	Pears
8083020	Fresh pear	Pears
8083090	Other fresh pears	Pears
8091000	Fresh apricot	Apricot
8092100	Fresh sour cherries	Cherries
8092900	Other fresh cherries	Cherries
8093000	Fresh peach, including fresh nectarine	Nectarine
8094000	Fresh plum and plum	Plums
8101000	Fresh strawberries	Strawberries
8104000	Fresh Cranberries	Cranberries
8132000	Prune lee	Prunes
10011900	Other durum wheat	Durum Wheat
10059000	Other corn	Corn

10061011	Glutinous rice paddy	Rice
10061019	Paddy rice	Rice
10061091	Other rice, rice	Rice
10061099	Other rice	Rice
10062010	Brown rice	Rice
10062090	Other brown rice	Rice
10063010	Glutinous rice	Rice
10063090	Other polished rice	Rice
10064010	Glutinous rice	Rice
10064090	Other broken rice	Rice
11029011	Glutinous rice flour	Rice
11029019	Other rice fine powder	Rice
11031921	Glutinous rice coarse grain and powder	Rice
11031929	Other rice coarse grains and powder	Rice
12019010	Yellow soybean	Soybeans
12019020	Black soybean	Soybeans
12149000	Carrots, feed, beef and other plants	Carrots
14042000	Cotton linters	Cotton
20089300	Cranberries made without vinegar	Cranberries
20091100	Frozen orange juice	Oranges
20091200	Non-frozen orange juice with a Brix value of up to 20	Oranges
24011010	Unstemmed flue-cured tobacco	Tobacco
24011090	Other unstemmed tobacco	Tobacco
24012010	Partial or full-stemmed flue-cured tobacco	Tobacco
24012090	Partially or fully drained tobacco	Tobacco
24013000	Tobacco waste	Tobacco
24031900	Other tobacco for smoking	Tobacco
24039100	Homogenization or Reconstituted Tobacco	Tobacco
52010000	Uncombed cotton	Cotton

Appendix E. Data Matching Procedure

To construct our primary outcome variable of interest, *Change in Tariffed Planting* and other variables included in the models, e.g. *Total Acres (kAC)*, *Conservation Reserve Program (%)*, we follow the steps below:

1. First, we obtain a full list of agricultural products that were targeted by Chinese tariffs which was announced on June 16, 2018 and took effect on July 6, 2018.[17]

2. Next we draw data from the US Department of Agriculture National Agricultural Statistics Service (USDA NASS)'s *Cropland Data Layer* (CDL). The CDL is a crop-specific land cover data based on satellite imagery (30m^2 spatial resolution). Each of these layers is a geo-referenced raster image that can be translated into annual estimates of crops planted within the geographical boundaries of each US county, excluding ones from Alaska and Hawaii. The CropScape further provides an Application Programming Interface (API) that allows interested users to download quantified estimates of crop planting from each defined area of the CDL.[18]

Using the CropScape API, we download county-level estimates of annual crop planting data for all 3,108 counties in the US between 2008 and 2020, each stored in comma-separated values (CSV) format. Each CSV file contains information on crop type (**Category**), number of pixels (**Count**) each corresponding to 30m×30m of land, translated acreage of these pixels (**Acreage**), and the USDA's own classification code for each crop type (**Value**), as presented in Table E.

3. We then match the items in the Chinese Ministry of Commerce's list with each crop types and their planted acreages in each county-year CSV file. For example, according to the tariff list, *Corn*, *Cotton*, *Soybeans*, and *Peanuts* in Table E are subject to Chinese tariffs. We sum these quantities to define planting acres of a given county-year observation. *Winter Wheat* and *Rye* are not subject to Chinese tariffs, but constitute total acres planted in the

[17]Ministry of Commerce, China, "Announcement on the imposition of tariffs on certain products originating in the United States," June 16, http://www.mofcom.gov.cn/article/ae/ai/201806/20180602756389.shtml (Accessed Jul 3, 2020). For an English equivalent of this list, see List 1 (Batch 1) in Chuck, Evan, David Stepp, Nicole Simonian, and Zhiwei Chen, "China Releases Product Exclusion Process for Certain U.S. Products Subject to Additional Retaliatory Tariffs," *International Trade Law*, May 15, https://www.cmtradelaw.com/2019/05/china-releases-product-exclusion-process-for-certain-u-s-products-subject-to-additional-retaliatory-tariffs/ (Accessed Jul 3, 2020). Note that List 1 (Batch 2) does not include agricultural items, and all of the items in List 2 (Batch 1, 2, 3, and 4) are those either 1) imposed after farmers have planted crops in 2019, or 2) those imposed 10% tariffs initially and later on were imposed full 25% tariffs. Thus, our primary items of interest are those only in List 1, Batch 1.

[18]For details on the *Cropland Data Layer*, see https://www.nass.usda.gov/Research_and_Science/Cropland/sarsfaqs2.php.

given county-year observation. Other lands such as *Clover/Wildflowers* and *Sod/Grass Seed* are not farmlands and thus not included in either Tariffed or Total Acres, but are used to compute the percentage of total land reserved for environmental protection, the *CRP* variable.

Raw CDL Data Structure				**Constructing Variables**		
Value	**Category**	**Count**	**Acreage**	**Tariffed Acres?**	**Total Acres?**	**Total Land?**
1	Corn	3087	686.5	✓	✓	✓
2	Cotton	42806	9519.8	✓	✓	✓
5	Soybeans	4836	1075.5	✓	✓	✓
10	Peanuts	1217	270.7	✓	✓	✓
24	Winter Wheat	2948	655.6	✗	✓	✓
27	Rye	8	1.8	✗	✓	✓
⋮	⋮	⋮	⋮	⋮	⋮	⋮
58	Clover/Wildflowers	57	12.7	✗	✗	✓
59	Sod/Grass Seed	756	168.1	✗	✗	✓
⋮	⋮	⋮	⋮	⋮	⋮	⋮
			Used For:	**ΔTariffed/ΔSoy**	**Total Acres**	**CRP**

Table E. Matching Autauga county (AL)'s 2017 Crop Planting Data with the Chinese Ministry of Commerce's Tariff List. Shaded cells indicate crop types and acres that were affected by the 2018 Chinese tariffs.

Appendix F. Correlation Plot

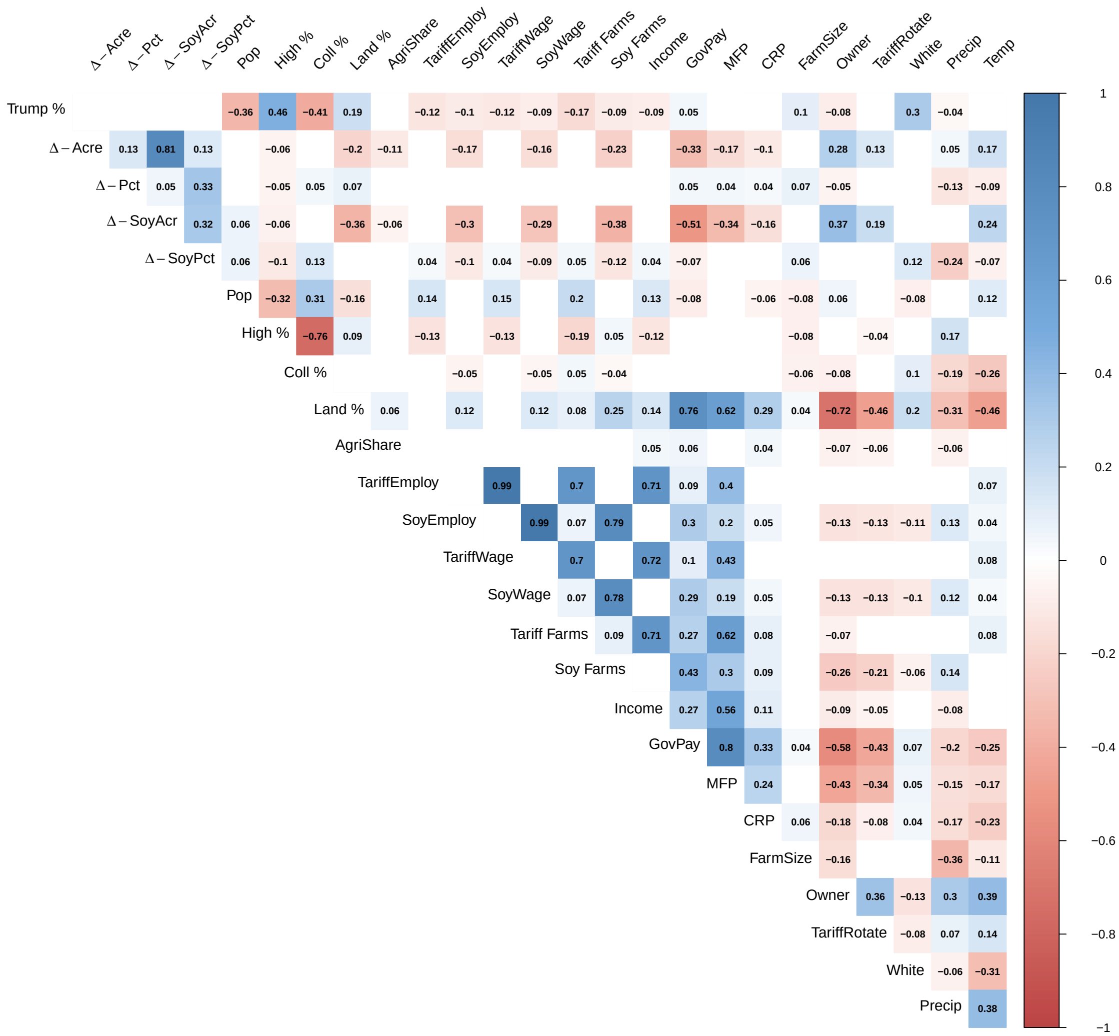


Figure F. Correlation Plot. This figure displays correlations between variables used in our analysis. Blue colors ranging between 0 and 1 indicate positive correlation and red colors ranging between -1 and 0 indicate negative correlation between two variables.

Appendix G. Full Regression Tables

	Dependent Variable:				
	Δ Tariffed Acres			Δ Soy Acres	
	(1)	(2)	(3)	(4)	(5)
Trump Share (%)	0.131***	0.131***	0.123***	0.102***	0.270***
	(0.028)	(0.026)	(0.028)	(0.019)	(0.044)
Planting Land (%)	0.213***	0.213***	0.212***	0.139***	0.287***
	(0.024)	(0.037)	(0.024)	(0.016)	(0.032)
ΔAgri-share (%)	−0.693***	−0.693***	−0.681***	−0.291***	−0.385***
	(0.067)	(0.150)	(0.067)	(0.044)	(0.078)
CRP (%)	−0.034	−0.034	−0.030	−0.087	−1.097***
	(0.248)	(0.491)	(0.247)	(0.161)	(0.339)
Rotatable	2.018**	2.018**	1.961**		
	(0.856)	(0.926)	(0.851)		
Rotatable (Soy)				3.330***	3.425***
				(0.772)	(1.094)
(log) Population	−0.045	−0.045	−0.032	0.254	2.475***
	(0.363)	(0.328)	(0.360)	(0.236)	(0.566)
High School (%)	−0.008	−0.008	−0.015	0.003	0.348***
	(0.084)	(0.079)	(0.082)	(0.054)	(0.117)
College (%)	0.074	0.074	0.065	0.029	0.383***
	(0.101)	(0.095)	(0.100)	(0.066)	(0.141)
Farm Income	0.00000	0.00000	0.00000	0.00000	−0.00002
	(0.00001)	(0.00001)	(0.00001)	(0.00000)	(0.00001)
Agri Employment (%)	−0.043	−0.043	−0.042	−0.038	−0.044
	(0.040)	(0.037)	(0.040)	(0.026)	(0.051)
Individual Farms (%)	−1.659*	−1.659***	−1.645*	−1.405**	−2.616**
	(0.919)	(0.560)	(0.915)	(0.597)	(1.320)
Gov. Payments	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.00004)	(0.0001)
MFP	0.257***	0.257***	0.255***	0.047	−0.082
	(0.077)	(0.082)	(0.076)	(0.039)	(0.122)
Tariffed Employment	0.002	0.002	0.002		
	(0.003)	(0.003)	(0.003)		
Tariffed Wage	−0.00000	−0.00000	−0.00000		
	(0.00000)	(0.00000)	(0.00000)		
Tariffed Farms	0.023	0.023	0.025		
	(0.018)	(0.017)	(0.018)		
Soy Employment				−1.091***	−0.978***
				(0.248)	(0.319)
Soy Wage				0.00003***	0.00003***
				(0.00001)	(0.00001)
Soy Farms				−0.910***	−0.069
				(0.239)	(0.340)
Avg. Farm Size	1.501***	1.501***	1.464***	0.832***	8.155***
	(0.323)	(0.466)	(0.320)	(0.210)	(1.045)
Avg. Ownership (%)	0.237***	0.237***	0.238***	0.131***	0.350***
	(0.024)	(0.025)	(0.024)	(0.016)	(0.037)
Avg. White (%)	−0.129**	−0.129***	−0.115**	−0.073**	−0.270***
	(0.056)	(0.049)	(0.056)	(0.037)	(0.100)
Avg. Precip.	−0.009**	−0.009**	−0.008*	−0.009***	0.006
	(0.004)	(0.003)	(0.004)	(0.003)	(0.007)
Avg. Temperature	0.213	0.213*	0.236**	0.244***	0.013
	(0.136)	(0.125)	(0.114)	(0.088)	(0.196)
Constant	−8.359	−8.359	−10.808	−11.453**	−60.082***
	(8.258)	(7.561)	(8.125)	(5.416)	(13.364)
Model	OLS	OLS	Mixed	OLS	OLS
Sample	Full	Full	Full	Full	SoyBelt
N	2,554	2,554	2,554	2,554	1,108
State FE	✓	✓	✓	✓	✓
F-Stats	29.68			45.48	50.41
Log Likelihood			−10,408.25		
AIC			20,864.51		
BIC			21,004.80		

*p<0.05; **p<0.01; ***p<0.005.

Table G1. Partisan Optimism on Tariff-affected Production. This table presents the OLS estimates of the effects of partisanship optimism on changes in tariffed crop planting. All regressions except Model 3 have state fixed effects. In Model 2, standard errors are clustered at state level.

	Dependent Variable:				
	Δ Tariffed Acres				Δ Soy Acres
	(1)	(2)	(3)	(4)	(5)
Trump Share (%)	0.003***	−0.299***	−0.005***	−0.073***	−0.196***
	(0.00000)	(0.001)	(0.00000)	(0.001)	(0.001)
Tariff	−0.119***	−0.005***	−0.230***	−0.115***	−0.041***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0004)
Planting Land (%)			0.027***	0.016***	
			(0.00000)	(0.00001)	
ΔAgri-share (%)			0.001***	0.00001***	
			(0.00000)	(0.00000)	
CRP (%)			0.020***	0.001***	
			(0.00000)	(0.00001)	
Rotatable			−0.153***	−0.025***	
			(0.00004)	(0.0001)	
(log) Population			0.148***	−0.445***	
			(0.00002)	(0.002)	
High School (%)			−0.00003***	0.275***	
			(0.00000)	(0.001)	
College (%)			−0.020***	−0.218***	
			(0.00001)	(0.003)	
Farm Income			0.00000***	0.0000***	
			(0.000)	(0.000)	
Agri Employment (%)			0.002***	−0.002***	
			(0.00000)	(0.00003)	
Individual Farms (%)			0.205***	−0.025***	
			(0.0001)	(0.0002)	
Gov. Payments			0.00002***	0.00000***	
			(0.000)	(0.000)	
MFP			−0.003***	0.001***	
			(0.00000)	(0.00000)	
Tariffed Employment			−0.0001***	0.00004***	
			(0.00000)	(0.00000)	
Tariffed Wage			0.000***	−0.000***	
			(0.000)	(0.000)	
Tariffed Farms			0.002***	0.0004***	
			(0.00000)	(0.00001)	
Soy Employment					
Soy Wage					
Soy Farms					
Farm Size			−0.026***	0.033***	
			(0.00003)	(0.0003)	
Ownership (%)			−0.015***	−0.001***	
			(0.00000)	(0.00001)	
White (%)			−0.003***	−0.0003***	
			(0.00000)	(0.00003)	
Avg. Precip.			−0.001***	−0.00001***	
			(0.00000)	(0.00000)	
Avg. Temperature			−0.008***	0.006***	
			(0.00000)	(0.00002)	
Trump Share×Tariff	0.006***	0.001***	0.003***	0.002***	0.002***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00001)
Constant	12.443***	26.224***	11.276***	9.523***	19.070***
	(0.0001)	(0.035)	(0.001)	(0.085)	(0.032)
N	15,530	15,530	10,338	10,338	15,530
Controls	✗	✗	✓	✓	✗
County FE	✗	✓	✗	✓	✓
Year FE	✗	✓	✗	✓	✓
Log Likelihood	−4,051,338,361	−22,833,012	−493,933,592	−8,473,181	−13,932,779
AIC	8,102,676,730	45,672,247	987,867,231	16,952,278	27,871,782

*p<0.05; **p<0.01; ***p<0.005.

Table G2. Partisan Optimism on Count of Tariff-affected Areas. This table presents estimates from poisson maximum likelihood models. Models 2, 4, and 6 have county and year fixed effects.

Appendix H. Spatial Dependence

	Dependent Variable: Δ Soy Acres					
	(1)	(2)	(3)	(4)	(5)	(6)
Trump Share (%)	0.102***	0.096***	0.102***	0.100***	0.102***	0.102***
	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)
Planting Land (%)	0.139***	0.14***	0.139***	0.144***	0.139***	0.139***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
ΔAgri-share (%)	-0.291***	-0.287***	-0.291***	-0.292***	-0.29***	-0.29***
	(0.044)	(0.044)	(0.043)	(0.043)	(0.043)	(0.043)
CRP (%)	-0.087	-0.1	-0.087	-0.118	-0.087	-0.086
	(0.161)	(0.161)	(0.159)	(0.158)	(0.159)	(0.159)
Rotatable (Soy)	3.324***	3.369***	3.324***	3.347***	3.325***	3.326***
	(0.773)	(0.779)	(0.762)	(0.768)	(0.762)	(0.762)
(log) Population	0.25	0.251	0.25	0.308	0.251	0.251
	(0.236)	(0.237)	(0.233)	(0.233)	(0.233)	(0.233)
High School (%)	0.003	0.006	0.003	-0.001	0.003	0.003
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)
College (%)	0.029	0.031	0.029	0.024	0.029	0.03
	(0.066)	(0.066)	(0.065)	(0.064)	(0.065)	(0.065)
Farm Income	0.0000	0.0000*	0.0000	0.0000*	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Agri Employment (%)	-0.038	-0.037	-0.038	-0.036	-0.038	-0.038
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Individual Farms (%)	-1.404**	-1.256**	-1.404**	-1.236**	-1.406**	-1.408**
	(0.598)	(0.601)	(0.589)	(0.588)	(0.589)	(0.589)
Gov. Payments	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MFP	0.047	0.04	0.047	0.04	0.047	0.047
	(0.039)	(0.039)	(0.038)	(0.038)	(0.038)	(0.038)
Soy Employment	-1.089***	-1.092***	-1.089***	-1.122***	-1.09***	-1.09***
	(0.248)	(0.249)	(0.244)	(0.245)	(0.244)	(0.244)
Soy Wage	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Soy Farms	-0.909***	-0.978***	-0.909***	-0.969***	-0.907***	-0.906***
	(0.239)	(0.24)	(0.236)	(0.236)	(0.236)	(0.236)
Avg. Farm Size	0.839***	0.81***	0.839***	0.887***	0.84***	0.84***
	(0.211)	(0.211)	(0.208)	(0.207)	(0.208)	(0.208)
Avg. Ownership (%)	0.131***	0.131***	0.131***	0.13***	0.131***	0.131***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Avg. White (%)	-0.072**	-0.065*	-0.072**	-0.07*	-0.072**	-0.073**
	(0.037)	(0.037)	(0.036)	(0.036)	(0.036)	(0.036)
Avg. Precip.	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Avg. Temperature	0.246***	0.247***	0.246***	0.253***	0.246***	0.246***
	(0.088)	(0.089)	(0.087)	(0.087)	(0.087)	(0.087)
Constant	-11.488**	-11.906*	-11.487**	-12.309**	-11.498**	-11.48**
	(5.42)	(6.214)	(5.349)	(6.132)	(5.346)	(5.353)
Model	OLS	SLX	SLM	SDM	SEM	SAC
N	2,483	2,462	2,552	2,552	2,552	2,552
ρ			0.00012174	-0.011918		0.0035959
λ					-0.002647	-0.006105
Log-Likelihood			-9140.452	-9099.065	-9140.448	-9140.443
AIC			18,423	18,476	18,423	18,425
F-Stats	45.46	35.24				

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

Table H1. Spatial Dependence (All US counties). This table presents results from a set of spatial econometrics models to adjust for spatial dependence. The baseline OLS in column (1) corresponds to Model 5 in Table 2 and Table G1. The rest of the results are estimated from *spatial lag X* (SLX, column 2), *spatial simultaneous autoregressive lag* (SLM, column 3), *spatial Durbin* (SDM, column 4), *spatial simultaneous autoregressive error* (SEM, column 5), *spatial autocorrelation* (SAC, column 6) models using R package spdep (Bivand, Pebesma and Gómez-Rubio, 2013), respectively. As shown above, the main results presented in Table 2 and Table G1 are robust after adjusting for spatial dependence. The estimated parameters ρ and λ in Models 3 through 6 are statistically insignificant, which imply weak spatial dependence in the data generating process.

	Dependent Variable: Δ Soy Acres					
	(1)	(2)	(3)	(4)	(5)	(6)
Trump Share (%)	0.271***	0.283***	0.271***	0.276***	0.276***	0.278***
	(0.044)	(0.044)	(0.043)	(0.043)	(0.043)	(0.043)
Planting Land (%)	0.287***	0.293***	0.287***	0.293***	0.286***	0.286***
	(0.032)	(0.032)	(0.032)	(0.031)	(0.032)	(0.031)
ΔAgri-share (%)	-0.384***	-0.359***	-0.384***	-0.364***	-0.384***	-0.386***
	(0.078)	(0.078)	(0.076)	(0.076)	(0.076)	(0.076)
CRP (%)	-1.097***	-1.237***	-1.097***	-1.27***	-1.189***	-1.259***
	(0.339)	(0.339)	(0.334)	(0.333)	(0.333)	(0.332)
Rotatable (Soy)	3.422***	3.509***	3.423***	3.33***	3.51***	3.538***
	(1.095)	(1.09)	(1.077)	(1.062)	(1.072)	(1.065)
(log) Population	2.475***	2.46***	2.476***	2.583***	2.514***	2.511***
	(0.566)	(0.565)	(0.557)	(0.549)	(0.555)	(0.552)
High School (%)	0.347***	0.332***	0.347***	0.362***	0.35***	0.352***
	(0.117)	(0.117)	(0.115)	(0.113)	(0.115)	(0.114)
College (%)	0.384***	0.395***	0.383***	0.404***	0.391***	0.403***
	(0.141)	(0.141)	(0.139)	(0.137)	(0.139)	(0.138)
Farm Income	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Agri Employment (%)	-0.044	-0.035	-0.044	-0.033	-0.038	-0.035
	(0.051)	(0.051)	(0.05)	(0.05)	(0.05)	(0.05)
Individual Farms (%)	-2.605**	-2.94**	-2.606**	-3.083**	-2.702**	-2.738**
	(1.321)	(1.321)	(1.299)	(1.284)	(1.293)	(1.284)
Gov. Payments	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MFP	-0.081	-0.129	-0.081	-0.15	-0.093	-0.102
	(0.122)	(0.122)	(0.12)	(0.118)	(0.12)	(0.119)
Soy Employment	-0.976***	-0.997***	-0.976***	-1.02***	-0.955***	-0.955***
	(0.319)	(0.319)	(0.314)	(0.308)	(0.313)	(0.312)
Soy Wage	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Soy Farms	-0.068	-0.059	-0.068	-0.047	-0.053	-0.05
	(0.34)	(0.338)	(0.334)	(0.328)	(0.333)	(0.331)
Avg. Farm Size	8.154***	8.28***	8.153***	8.454***	8.126***	8.109***
	(1.045)	(1.043)	(1.028)	(1.011)	(1.025)	(1.019)
Avg. Ownership (%)	0.35***	0.36***	0.35***	0.365***	0.353***	0.355***
	(0.037)	(0.037)	(0.037)	(0.036)	(0.037)	(0.036)
Avg. White (%)	-0.272***	-0.269***	-0.272***	-0.248**	-0.275***	-0.276***
	(0.1)	(0.1)	(0.099)	(0.097)	(0.098)	(0.098)
Avg. Precip.	0.007	0.006	0.007	0.007	0.007	0.008
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Avg. Temperature	0.01	0.016	0.01	0.006	-0.023	-0.034
	(0.196)	(0.195)	(0.193)	(0.189)	(0.192)	(0.191)
Constant	-59.953***	-50.755***	-59.94***	-54.525***	-60.906***	-62.062***
	(13.373)	(14.972)	(13.161)	(14.536)	(13.104)	(13.033)
Model	OLS	SLX	SLM	SDM	SEM	SAC
N	1,071	1,050	1,107	1,107	1,107	1,107
ρ			0.0016476	0.020882		-0.072845
λ					0.076156	0.1469
Log-Likelihood			-4,223.454	-4,188.832	-4,222.241	-4,221.14
AIC			8,522.9	8,523.7	8,520.5	8,520.3
F-Stats	50.34	33.01				

*p<0.05; **p<0.01; ***p<0.005.

Table H2. Spatial Dependence (US soybean belt counties). This table presents results from a set of spatial econometrics models to adjust for spatial dependence. The baseline OLS in column (1) corresponds to Model 6 in Table G1. The rest of the results are estimated from *spatial lag X* (SLX, column 2), *spatial simultaneous autoregressive lag* (SLM, column 3), *spatial Durbin* (SDM, column 4), *spatial simultaneous autoregressive error* (SEM, column 5), *spatial autocorrelation* (SAC, column 6) models using R package spdep (Bivand, Pebesma and Gómez-Rubio, 2013), respectively. As shown above, the main results presented in Table 2 and Table G1 are robust after adjusting for spatial dependence. The estimated parameters ρ and λ in Models 3 through 6 are statistically insignificant, which imply weak spatial dependence in the data generating process.