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 and resulting in a large number of agricultural bankruptcies. Why did some farmers disregard their own economic interests and plant low-value crops during the trade war? We argue that political preferences partially explain farmer behavior. Matching geo-referenced crop data to product-level sanctions lists from China, we calculate county-level changes in the 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 finds that ideological preferences can spill over into economic behavior. Much of this work focuses on the social aspect of consumer 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). However, much of the evidence for the phenomenon is either self-reported or reflects low-stakes survey environments. Does the effect of partisanship on economic behavior extend to large-scale business decisions, such as business owners' production of 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 consumers make marginal decisions based on ideological preferences. The societal costs of polarization are much higher if business owners are willing to make partisan decisions that may not even benefit their economic interests.

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 et al. 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 large-scale production decisions can follow partisan patterns. Specifically, 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 benefit an in-group or harm an out-group. This suggests that partisanship may affect more decisions than previous 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 farmers' 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 negatively impacted by Chinese tariffs. This is despite the fact that many of these crops plummeted in value.[1] In contrast, farms 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 into farmers' planting decisions.

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

Within the trade politics literature, this paper contributes to answering two lingering questions. First, much literature has noted that trade preferences often do not appear to be driven by economic 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), others 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 rules out cheap talk.

Second, the so-called "China Shock" (Autor et al. 2013) from the early 2000s is well known to have domestic political outcomes in the United States. The consensus is that exposure to severe import competition from China introduced a negative and lasting impact on local economies in the US, thereby

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

increasing support for Republicans and protectionist trade policies (Autor et al. 2020; Kuk et al. 2018; Feigenbaum and Hall 2015). Other work has highlighted the political consequences of the US-China trade war (Chyzh and Urbatsch 2021; Blanchard et al. 2024). Still others have shown politicized determinants of which products were targeted by China in the first place (Fetzer and Schwarz 2021; Kim and Margalit 2021), suggesting that the tariffs themselves were politically targeted.

The literature clearly suggests that political polarization can be connected with trade. Import competition with China has been linked with political outcomes (Autor et al. 2020), and government responses to trade shocks are often politicized (Kim 2024; Kim and Pelc 2021a,b). Yet, the economic causes and consequences of these politicized outcomes have not been fully explored. In the context of the agricultural industry during the US-China trade war, we examine the impact of political preferences on economic behavior.

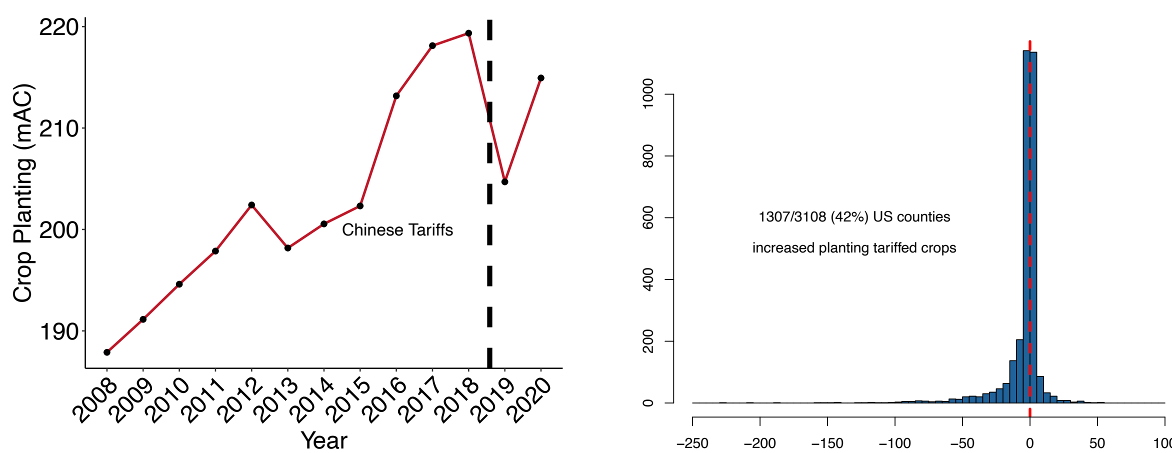
In the remainder of this paper, we develop and test a theory of partisan economic behavior during the US-China trade war. In Section **2**, we further expand upon the motivation of the paper by examining data from the US-China trade war. In Section **3**, we develop the theory, drawing from literature on affective polarization and economic behavior. In Section **4**, we introduce the original data 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 by considering the more significant implications of this research.

2 The US-China Trade War

In March 2018, the United States increased tariffs on Chinese steel and aluminum products following the previous year's investigations by the Department of Commerce under the Trade Act of 1962. China responded by imposing retaliatory tariffs on various US products, including aluminum, pork, fruits, and nuts. This led to a full-fledged trade war, with each country imposing up to fifty billion dollars' worth of tariffs on 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 (USDA 2019, 36).

The US agricultural industry suffered severe economic losses during the trade war. US farms' sales to China plummeted, going down from 19.5 billion US dollars in 2017 to 9.1 billion US dollars in 2018 (USDA 2022a,b). Farm bankruptcies increased by 20% in 2019 compared to those of the previous year (US Courts 2018, 2019).[2] Moreover, expectations for the trade war to intensify grew after the two countries exchanged additional tariffs between July and September 2018.

The uncertainty in sales and export prices prompted many US farmers to switch planting from dominant crops like soybeans to other crops not targeted by Chinese tariffs. However, not all farmers reacted identically to the tariffs. **Figure 1** shows that while 2019 witnessed a steep overall decline in the planting of crops that were subject to Chinese tariffs, significant variation exists in how farmers reacted. In fact, about 42% of US counties *increased* planting of crops targeted by China's retaliatory tariffs compared to the previous year.[3]



(a) Trend in Tariffed Crop Planting (b) Δ County-level Planting in 2019

Figure 1. Changes in Tariffed Crop Planting in the United States. This figure displays planting trends and changes in crop planting (in million acres and %) 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. Thus, we exclude these two states from our analysis. Panel (a) displays a steep decline in crop planting (in million acres) in 2019 that was targeted by the 2018 Chinese tariffs, which bounced back in 2020. Panel (b) shows that about 42% of US counties have increased planting such tariffed crops in 2019. **Online Appendix C** provides a complete list of crops subject to Chinese tariffs.

[2] The number of annual bankruptcy filings under Chapter 12 has been traditionally used to measure farm bankruptcy in the United States. 498 cases were filed under Chapter 12 in 2018, which increased to 599 cases (20%) in 2019.
[3] **Online Appendix B** shows the variation of tariffed crops and soybean planting changes in 2019.

Why did some farmers respond in a way that made them vulnerable to the trade war while others did not? Much of the explanation is economic. Some of the variation in crop planting during the US-China trade war can be explained through agriculture's unique characteristics.

Unlike the manufacturing sector, agriculture production relies directly on weather conditions and soil quality. Thus, a farm's location partially determines the type and the number of crops a farmer can plant and the farmer's response to unexpected price shocks.

Agricultural subsidies also play a role in farmers' calculations. The US has long been a user of subsidies to assist the farm industry in managing economic downturns. Adding to existing subsidies, the Trump administration launched the Market Facilitation Program (MFP), a massive compensation program to offset the financial losses that the agricultural industry experienced during the trade war. The USDA calculated 2018 MFP payments through a formula that included estimated losses for various crops and repaid farmers by bushel or acre of production (Paulson et al. 2019). The 2019 rates were calculated at the county level, based on the historic production of affected crops, and paid to farms at a per-acre rate.

Though the MFP and other subsidies provided much-needed help to farmers, the payments were not enough to prevent the large-scale bankruptcies mentioned above.[4] In 2018, roughly 8.6 billion US dollars were paid to farmers through the MFP, which increased to 14.5 billion in 2019. This large number of agricultural subsidies may have been one factor that enabled some farmers to maintain their crop planting practice. That said, MFP payments are a post-treatment control, and the government may have directed them partially as a result of the planting of tariffed crops. This would create an inferential concern. We cannot rule out MFP-related motivations, but we also cannot entirely depend on the MFP driving farmers' decision-making.[5]

[4] Some also fault the USDA's calculations for prioritizing larger farms (Pamuk 2019).

[5] In **Online Appendix G, Table G1**, we show that including MFP payments and other government subsidies as controls in our models does not significantly alter the values of our primary empirical results. We also conduct a causal mediation analysis in **Online Appendix H** to address the potential mediating effect of the MFP payments on crop planting decisions. The results from **Online Appendix G**, **Table G1** and **Online Appendix H** combined show that the MFP did not have a significant mediating impact on farmers' crop planting choice, indicating the robustness of our primary results presented in the empirical section.

Regardless, the existence of government subsidies does not explain farmers' willingness to take economic losses above and beyond government compensation. This suggests that farmers' responses to the trade war may not have been entirely a reflection of their economic calculations. Anecdotal evidence indicates that this puzzling behavior may also be related to ideological beliefs (Evers-Hillstrom 2019). Farmers may have been abandoning their well-being for ideological reasons, similar to soldiers on the battlefield. 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).

Previous literature suggests that Americans' self-professed beliefs are often politically motivated. Scholars have long argued that partisanship can serve as a "perceptual screen" through which people view economic facts (Campbell et al. 1960, 133). For example, perceptions about economic outlooks 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 et al. 2015). However, as Bisgaard (2019) notes, even when individuals are provided with the correct information about economic trends, they often 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 performed better in a copyediting task when they believed they were doing work for co-partisans. But this hardly rises to the production level relevant to the question of agricultural firms.

Elite cues can be powerful drivers 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 1992; Page et al. 1987). This is especially true in foreign policy: Rho and Tomz (2017) suggest that non-material trade preferences are often driven by elite cues.

There is much reason to believe that partisan cues could be especially influential in trade policy. The international political economy literature has long questioned the direct role of self-interest in determining people's preferences over trade (Sabet 2016; Lü et al. 2012; Mansfield and Mutz 2009; Rankin 2001) and foreign policy more generally (Guisinger 2017; Berinsky 2007). For example, Mutz and Kim (2017) argues that out-group antipathy can be a driver of trade preferences. Much of this work focuses on low-information environments. Because most Americans have little reason to think much about trade, they are more likely to outsource information gathering to elites they trust. In contrast, individuals with higher levels of information and education are more likely to link their self-interest to trade preferences (Hainmueller and Hiscox 2006).

What the previous literature has not demonstrated is the strength of politically motivated beliefs and preferences. Much of this work, especially in trade and foreign policy, has derived preferences from low-stakes survey environments. It has been difficult for the literature to find high-stakes examples of politically derived trade preferences. Unlike random survey respondents, US farmers have every reason to collect all the information they can about imports and exports before making high-risk decisions. If they nevertheless are drawing from partisan cues, partisanship may be an even stronger cue than previous literature has suggested. With its politicized origins and clear economic effects, the US-China trade war provides an ideal venue to probe the limits of partisan economic behavior.

3 Theory

We argue that political beliefs, driven by elite cues, partially drove variation in farmers' planting decisions at the onset of the US-China Trade War. Under uncertainty, people draw from various information sources to predict the future and choose the best course of action. One powerful source of this information can come from the word of trusted authorities. Although previous research shows that political elites can drive preferences in low-stakes environments, we argue that this can even be the case for high-stakes decisions that affect someone's economic livelihood. Political cues can be powerful drivers of high-stakes economic activities.

Farmers, like many business owners, are accustomed to making decisions under uncertainty. Each season, farmers have to predict the unpredictable, including factors like weather, market conditions, input costs, competition, and local and national regulations. This uncertainty is not new, and many tools exist to help farmers make these predictions. Farmers' almanacs, weather and climate reports, futures markets, insurance plans, and government risk assessments can help farmers decrease familiar forms of uncertainty.

Understandably, farmers are not as well versed in navigating uncertainty regarding geopolitical trade conditions. They have no almanac for, and very little experience in, predicting the outcomes of trade negotiations. Therefore, they have every incentive to collect and interpret every piece of information they can access. Predicting geopolitical events became especially important during the first months of the US-China Trade War when China heavily tariffed the importation of many US crops. At the time, the future was murky: would the trade war end quickly, leading to business as usual? Or would it become necessary to invest in a new, post-tariff economy?

The trade war left farmers with a familiar dilemma in an unfamiliar environment. If they continued planting tariffed crops, and the trade war came to a quick end, then the season would have been a success. On the other hand, investing in new crops would involve a costly start-up process, requiring new technology, equipment, and storage practices (Weinraub 2019). This investment would only be worthwhile if the trade war turned out to be difficult to resolve. The decision to continue planting tariffed crops was essentially a bet that the trade war would end quickly.

The literature reviewed in the previous section suggests that elite cues are crucial in helping people develop opinions and beliefs in unfamiliar conditions, including in foreign policy. This should be no different for farmers, who have little expertise in the subject. Trade war is an especially unpredictable area of foreign policy—even experts have difficulty agreeing on when and how they will end. This makes elite cues potentially more important than ever.

If farmers wanted to seek elite cues during the US-China trade war, President Donald Trump was an obvious choice. He was the one who started the trade war in the first place and was one of few people with the power to end it. Therefore, when farmers had questions about when the trade war was likely to end, Trump was a reasonable person to look to. And he certainly had plenty to say about it. In speeches across the country, he consistently projected optimism, claiming that "you're going to be so happy. You're going to be so happy" (Long 2018). 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 quickly bounce back.

In the first month of the trade war, when farmers were making crucial planting decisions, many relied on Trump's statements as evidence that it was safe to continue planting tariffed crops. Journalistic accounts provide qualitative support for this assertion (Lobosco 2019). According to a 2018 interview with a Kansan farmer regarding planting decisions, "Everyone will have a different take…Some will use market advisory services. Some depend on political persuasion, how much he trusts or doesn't trust what this administration is promising to deliver" (Cohen 2018). Another farmer and Trump voter justified his faith in the administration, adding "I guess you got to be an optimist. If you farm you got to be an optimist" (Jacobs 2018). Other farmers were willing to provide the benefit of the doubt to the Trump administration, but only in the short term, suggesting "I think [the trade war] is worth it…If it continues in the next couple of years, call me back" (Meyer 2019).

Farmers were not alone in looking to the former president for guidance. Trump's supporters often believe his rhetoric, across many fronts. Polls suggest that up to 71% of Trump voters believe that what he tells them is true—higher than the same voters' beliefs in their own friends and family (63%) (Lawler 2023). This variation is borne out through surveys of farmers themselves. According to a 2019 survey by Qu et al. (2019), nearly 60% of farmers were supportive of the tariffs against China, while 30% opposed them. This also tracks with these farmers' information environments: FOX News was the most-cited information source, followed by farm bureaus. Although we do not have the data to test this, it is likely that this information environment—especially viewership of FOX News—informed these decisions and may have further reinforced some farmers' choice of elite cues. In a separate study, Viskupič et al. (2022) show that farmers who identify as Trump voters are the ones most likely to express support for protectionist trade policies.

If all farmers were to take the president's words to heart, then China's tariffs would have little effect on planting—everyone would expect the trade war to come to a quick and profitable end. However, despite being president, Trump was also a polarizing figure. As the quotations above suggest, not all farmers were equally likely to trust the former president's word. Farmers varied in their likelihood of adhering to this specific elite cue. This variation, we argue, should drive variation in farmers' behavior.

Farmers who were more inclined to trust the president should be more likely to believe that the trade war would be short-lived and lead to higher prices of tariffed goods in the immediate future. These farmers were likely to believe they would be better off planting crops that were affected by the trade war, with the expectation that those who bet on a swift win would be better off than those who did not. The fact that some farmers decreased their reliance on crops affected by the trade war may have *further* incentivized pro-trade-war farmers to increase their tariffed crop production: a decrease in supply elsewhere might make the potential profit even higher.

In contrast, those who were less ideologically inclined to follow Trump's lead may have been more likely to believe that the trade war would not end soon and would not result in a better economic position for US producers. Once again, these beliefs affect farmers' utility calculations by shaping their expectations of future benefits. Instead of doubling down on tariff-affected crops, these farmers might overcorrect in the opposite direction. For example, they might make large investments in equipment and storage technology that is only useful for non-tariffed crops, effectively insuring against a long trade war. Although we do not have individual-level data on Trump support, we can proxy for an individual's Trump support using county-level data. Certainly, some of Trump's 2016 vote-share came from an aversion to his opponent rather than full-on support for Trump. Therefore, Trump vote-share is only a proxy for farmer support. However, voting for Trump is at least indicative of a willingness to take cues from him. These political expectations lead to the hypothesis below.

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

Looking to political elites like President Trump to make important decisions under uncertainty is consistent with a self-interested cost-benefit calculation. However, an alternative explanation could suggest a second mechanism: the use of business practices as expressive signals. Instead of making instrumental business calculations, some farmers could be reacting personally to the trade war and planting tariffed crops as a show of support for their preferred party.[6] This need not be wholly emotional: insofar as farmers reap social capital for displaying Republican support, they may be likely to show their support using their fields as symbols. When homeowners display lawn signs to express support for their preferred candidate, they enjoy 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 et al. 2008). Planting tariffed crops could be taking a form analogous to a giant lawn sign for some farmers.

These two mechanisms are difficult to disentangle empirically. If we had farm-level information on which properties are more likely to be visible to neighbors, then perhaps we could distinguish between visible and invisible fields. But absent that kind of data, the distinction is difficult. That said, the qualitative record supports the elite cues explanation over the social pressure mechanism. We have not found any journalistic accounts of farmers trying to appeal to their peers through expressive political acts. In fact,

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

many interviews suggest the opposite: farmers and their peers openly and politely disagreed about the proper course of action, suggesting that there was little pressure to display partisanship through crops.

A second hypothesis can provide a partial test of this alternative explanation. We argue that the social pressure mechanism would be more likely in a place with high Republican support, especially support during the most recent (2018) election. Rather than a proxy for belief in Trump's rhetoric, support for the Republican party in 2018 is a more general measure of an area's political partisanship at the time the trade war began. Therefore, if social pressure were driving farmer behavior, then planting of tariffed crops should be high in counties with high Republican vote-share at the time of the tariff announcements. Although this is an imperfect test, and it is still quite possible that both mechanisms are working together to drive farmers' crop planting decisions, this leads to a second hypothesis.

HYPOTHESIS 2 *The more a population supports its 2018 Republican House candidate, the more likely its farmers will maintain their planting of tariff-affected goods during the trade war.*

Based on the qualitative record, we do not expect to find support for this alternative hypothesis. Using novel observational data, we test the above hypotheses of agricultural behavior and political preferences. Below, we outline the data we collected and the methods used to test this theory and determine the relationship between political preferences and costly economic behavior.

4 Data

4.1 Support for Trump and US Agricultural Production

We link several agricultural, political, and economic databases to test our argument on the effects of farmers' support for Trump on their economic behavior during the US-China trade war. First, we collect annual county-level planting records from the US Department of Agriculture (USDA)'s Cropland Data Layer

(CDL) application programming interface (USDA 2012). The CDL provides geo-referenced crop-specific land cover data based on satellite imagery.

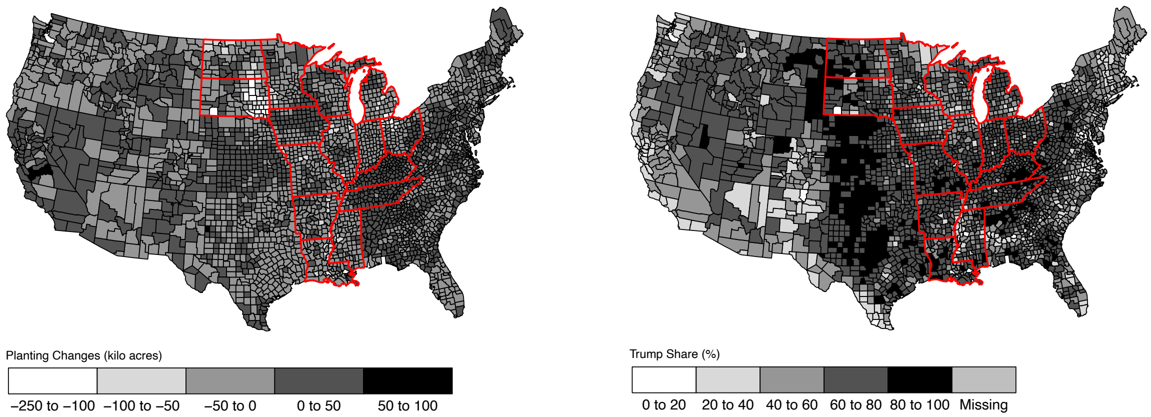
Using the CDL data, we construct our outcome variable of interest: county-level measures of annual *changes in crop planting* of agricultural goods exposed to Chinese tariffs. We are particularly interested in whether or not farmers decreased their reliance on goods hit by tariff shocks from China between 2018 and 2019. We first computed annual volumes of tariff-exposed crops and calculated their annual change. We then hand-coded the list of items subject to the 2018 tariffs announced by the Chinese Ministry of Commerce to calculate these numbers accurately.[7] We then matched each agricultural item on this list to the CDL data based on agricultural product codes defined by the USDA.[8]

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 county-level changes in crop planting exposed to Chinese tariffs between 2018 and 2019.[9] The area outlined in red represents the top 15 soybean-producing states (i.e., the "soybean belt"). We expect these states to be the most heavily affected by the trade war.

[7] See **Online Appendix C** for a full list of agricultural products that we include to construct our measure. 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.

[8] See **Online Appendix D** for details of the matching procedure.

[9] 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.



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

Figure 2. The Geographical Distribution of Support for Trump and the 2018-2019 Changes in Crop Planting Exposed to Chinese Tariffs. This figure displays county-level variation in Trump support (%) and changes in tariffed crop planting (kilo acres). Panel (a) presents county-level changes in tariff-exposed crop planting between 2018 and 2019. Panel (b) presents the geographical distribution of Trump's vote share in the 2016 Presidential election across US counties. In Panel (a), moving from lighter to darker counties indicates an increase in the volume of tariff-exposed crop planting (in kilo acres). In Panel (b), moving from lighter to darker counties indicates greater vote shares for Trump in 2016. The red lines indicate the top 15 soybean-producing states.

The primary independent variable of interest is a county-level measure of support for Trump: *Trump's vote share* in the 2016 presidential election.[10] The second panel in **Figure 2** displays the geographical distribution of Trump's vote share across US counties.

4.2 County Characteristics

Next, we consider a battery of economic factors to account for potential confounders of farmers' crop planting decisions in the pre-planting season. We collect annual county-level data for most of these factors from the US Bureau of Economic Analysis (BEA) regional economic accounts database.[11] We adjust for county size and the importance of the agricultural industry with (log) *population*, the share of land used for agricultural production (*planting land, %*), change in agricultural industry's share of the economy (*Δ agri-share, %*), and the number of affected farms (*tariffed farms*). Second, we consider the amount of land

[10] Data from the CQ Voting and Elections Collection (CQ Press 2020). Because the Cropland Data Layers do not provide estimates for Alaska and Hawaii, we exclude election results from both states.
[11] https://www.bea.gov/data/economic-accounts/regional.

previously reserved for environmental protection via the Conservation Reserve Program (*CRP*).[12] Finally, farmers rotate different types of crops in the same area of land over time to maintain soil fertility and maximize their yield, depending on the qualitative difference in soil conditions (Aguilar et al. 2015; Roesch-McNally et al. 2018). We consider *crop rotation* to account for farmers' ability to switch to other crop types under the tariff shock.[13]

In addition, we use the USDA's 2017 Agricultural Census data (USDA 2017) to collect average *farm size* (thousand acres), the average proportion of farms operated based on full *ownership* (%), and the average share of farms with *white* owners (%) in each county. We also adjust for county-level educational attainment using the portion of the adult population with at least a high school degree (*high school*, %) and a bachelor's degree (*college*, %) using the American Community Survey data (US Census 2018).

4.3 Weather Conditions

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 farmers' 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 2023). This dataset contains daily precipitation levels and minimum/maximum temperature for each predefined grid covering the entire US territory, which is then aggregated at the county level. We rely on Schlenker (2023)'s

[12] 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. Farmers are more likely to increase planting when these grants end, as many did in 2019. For details, see https://www.fsa.usda.gov/programs-and-services/conservation-programs/conservation-reserve-program/.

[13] Specifically, we use the Shannon-Wiener Index (Pielou 1966), a widely used measure of crop diversity $H = -\sum_{i=1}^{S} p_i \times \ln p_i$, where S is the total number of crop types planted in each county in the last year, p_i is the proportion of the total area occupied by the ith crop in the previous year. A higher Shannon-Weiner Index indicates greater crop diversity in a county, meaning farmers can more easily switch to non-tariffed crops.

algorithm to compute the average daily temperature and precipitation levels given temperature bounds in the data.[14] **Table 1** presents the summary statistics.[15]

Statistic	N	Min	Q1	Med	Mean	Q3	Max	St. Dev.
Trump Share (%)	3106	4.1	54.6	66.4	63.3	74.9	94.6	15.6
Δ Tariffed Planting	3108	-229.1	-3.6	-0.1	-4.7	0.4	50.8	17.1
Δ Soy Planting	3108	-147.5	-4.4	-0.2	-4.7	0.0	19.9	12.2
Tariffed Planting$_{t-1}$	3108	0.0	2.2	22.3	70.6	105.4	849.3	100.9
Tariffed Soy Planting $_{t-1}$	3108	0.0	0.0	2.6	30.4	41.5	487.3	52.2
Planting Land (%)	3108	0.0	3.8	16.1	27.2	47.5	93.1	27.3
Δ Agri-share (%)	2724	-32.3	-0.7	0.0	-0.2	0.3	58.7	4.4
CRP (%)	3067	0.0	0.0	0.9	7.4	6.5	261.1	18.3
Crop Rotation	3108	0.0	0.8	1.0	1.0	1.3	1.6	0.3
(log) Population	3055	4.2	9.3	10.2	10.3	11.1	16.1	1.5
High School (%)	3108	7.3	29.7	34.5	34.2	39.1	57.4	7.2
College (%)	3108	0.0	10.1	13.2	14.2	17.3	45.4	5.7
Farm Income	3055	-55453.0	491.0	7292.0	20908.9	21694.0	1629209.0	75297.4
Agricultural Employment (%)	3055	2.2	21.4	27.4	28.7	34.3	64.4	9.5
Tariffed Farms	3108	0.0	0.0	2.0	8.7	7.0	842.0	30.0
Farm Size	3055	0.0	0.2	0.3	0.7	0.5	58.5	1.7
Ownership (%)	2927	0.0	22.9	38.4	39.2	53.0	100.0	19.1
White (%)	3068	0.0	96.8	99.1	96.5	99.8	100.0	7.7
Precipitation	3035	11.6	106.9	185.5	203.2	264.4	777.5	126.2
Temperature	3035	-17.4	-4.4	1.7	1.4	7.5	21.0	7.7

Table 1. Summary Statistics.

5 Empirical Findings

We evaluate **Hypothesis 1** by examining the relationship between county-level support for Trump and crop planting behavior. First, we run a set of ordinary least squares (OLS) regression models on cross-sectional data to examine whether counties made different planting decisions in response to the tariff shock between

[14] Note that successful annual crop yield depends on 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 crop they choose. The resulting measures in our models are based on optimal temperature/precipitation bounds for soybeans, a crop central to our analysis.
[15] **Online Appendix E** provides correlations among these variables.

2018 and 2019. Second, we look to a difference-in-difference design to determine the impact of the 2018 tariffs in counties with varying levels of Trump support.

5.1 Trump Support and Economic Responses

Our first model uses the following specification,

$$Y_i = \alpha + \beta X_i + \gamma^\top Z_i + \delta_s + \epsilon_i$$

where the outcome variable of interest, Y_i is the change in crop planting (kilo acres) exposed to Chinese tariffs between 2018 and 2019 and X_i is *Trump's vote share* in the 2016 US presidential election. We measure both variables at the county level. Next, $\boldsymbol{Z}_i$ constitutes a vector of county-level characteristics described in the previous section. We also add commuting-zone fixed effects (δ_s) to account for unobserved confounders.[16]

The primary quantity of interest is β, which we expect to be positive and statistically significant. This indicates that counties that support Trump more, on average, will *increase* their planting of crops 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 crops after the tariffs were announced.

Table 2 presents the main findings from OLS regression models with several subsets of the data. Model 1 shows the baseline result on the effect of support for Trump on crop planting changes across all

[16] Commuting zones (CZs) are designed to represent local labor markets more accurately than traditional administrative boundaries like counties or metropolitan areas. They reflect the economic dependencies across regions where people typically commute for work (Tolbert and Sizer 1996). We match each US county to 609 commuting zones using the 2010 county-CZ walkthrough data from the Penn State Commuting Zones/Labor Markets data repository (https://sites.psu.edu/psucz/) to account for the impact of unobserved CZ-level confounding factors on crop plantation. In **Online Appendices I and J**, we provide more conservative standard errors of the baseline models with alternative inference methods such as wild bootstrap inference (Roodman et al. 2019) and Conley standard errors (Conley 1999), which are widely used remedies for conventional inference in cases where the number of clusters is small or when there are potential spatial spillovers between units.

tariff-exposed crops. In Model 2, we limit our sample to 'soybean belt' states, the fifteen states producing the most soybeans. In Model 3, we run the same model to states that exported agricultural products the most to China in 2017.[17] Standard errors are clustered at the commuting zone (CZ) level. Note that samples in all models are restricted to counties with at least one farm producing tariff-exposed items (e.g., soybean). Consistent with our expectations, the correlations here are positive and statistically significant.

	Dependent Variable:					
	Δ Tariffed Acres			Δ Soy Acres		
	(1)	(2)	(3)	(4)	(5)	(6)
Trump Share (%)	0.157***	0.187***	0.163***	0.100***	0.213***	0.210***
	(0.034)	(0.069)	(0.062)	(0.021)	(0.048)	(0.048)
Sample	Full	Soy Belt	China	Full	Soy Belt	China
Observations	1,934	827	514	1,934	827	514
Controls	Yes	Yes	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.683	0.752	0.726	0.799	0.796	0.767
F-Stats	8.57	11.86	9.20	14.99	14.96	11.15

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

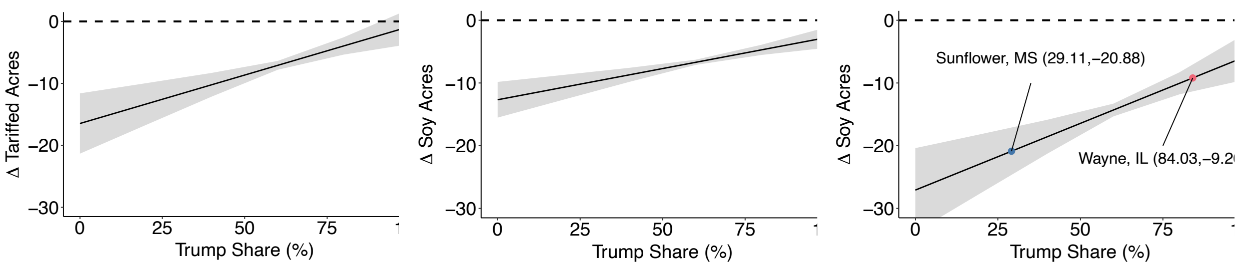
Table 2. Support for Trump on Tariff-affected Crop Planting. This table presents the ordinary least squares estimates of the effects of support for Trump on changes in tariff-exposed crop planting. Models 2 and 5 limit samples to counties in the soy-belt states. Models 3 and 6 limit samples to counties in states whose top exporting country was China in 2017. All models include commuting zone fixed effects. Full regression results are available in **Online Appendix G, Table G1**.

The results combined suggest that Trump's vote share is strongly associated with changes in crop planting behavior in the year following the imposition of Chinese retaliatory tariffs. The first row of Models 1 to 3 shows that a one-percentage-point increase in Trump's vote share in the 2016 presidential election translates to about a 100 to 200-acre increase in the planting of crops affected by Chinese tariffs. Therefore, a one-standard-deviation increase in Trump vote share (15%) could increase tariff-affected crop planting

[17] These 12 states are Alabama, Illinois, Indiana, Louisiana, Mississippi, Nevada, New Mexico, North Carolina, Ohio, Utah, Virginia, and Washington. Top China-exporting states are identified using HS-6 digits level data from USA Trade Online (https://usatrade.census.gov). We sum up export values of all tariff-exposed items listed in **Online Appendix C** by their export destination in 2017 and divide it by the total value of agricultural export (HS 07, 08, 10, 11, 12, 13, 14, 20, 24, 52) in 2017. This returns the ratio of the export value of the item to the total agricultural export for a given country. Finally, we selected only the most exported item-country pair for each state and chose states whose favorite trading partner was China in 2017. The top trading partners of these 12 states are detailed in **Online Appendix F**.

by up to 2,400-2,800 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.

We further test the robustness of our primary findings by running the same set of models using soybean-specific data rather than aggregating all tariff-exposed goods. Soybeans are one of the most heavily affected crops during the trade war because 60% of US soybean exports before the trade war went to China (Hart and Schulz 2015). Therefore, if anything, we expect β to be more significant when we isolate the effect on soybeans. The substantive effects become larger in the soybean-specific models 4 to 6 that isolate changes in soybean planting as the outcome measure. Model 4 shows that across all US counties, a one-percent increase in Trump's vote share translates into an increase of 100 soybean acres. However, Models 5 and 6 indicate that counties in the 'Soy Belt' states and top China-exporting states show an increase in 213 and 210 soybean acres, respectively.[18]



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

Figure 3. Predicted Changes in Crop Planting by Trump Support. This figure presents predicted changes and confidence intervals with 95% confidence in crop planting volumes by Trump vote share. Each panel is based on results from Columns 1, 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% 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 significant. For example, based on results from Panel (c), counties in the

[18] To adjust for potential confounding effects of agricultural subsidies, we include the Market Facilitation Program (MFP) payments and other agricultural subsidies in the baseline models. The results in **Online Appendix G, Table G2** show that the baseline results remain mostly the same even when controlling for these factors. In **Online Appendix H**, we run a causal mediation analysis to further show that the MFP did not significantly impact farmers' crop planting behavior.

soy belt that exhibit extreme support for Trump, such as Wayne, Illinois (84.03%), were likely to plant about 10,000 acres of soybean more than their Democratic counterparts, such as Sunflower, Mississippi (29.11%) during the trade war. Given that the average US soy planting in 2019 was around 25,000 acres and 49,000 acres in Soybean belt states, respectively, the 10,000-acre difference between extreme Republican counties and Democrats is quite substantial.

5.2 Difference-in-Differences

Next, we check the robustness of the support for **Hypothesis 1** through a set of regression models that consider the *interaction* between support for Trump 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 using data between 2008 and 2021. The outcome variable in these models is the *count* of areas of tariff-exposed crops planted in a county.[19] We add a binary indicator representing the tariff shock, coded as zero (0) in 2018 and before the trade war and one (1) from 2019 onward, during the trade war.[20] To calculate the politicized differences in planting behavior, we interact the tariff shock variable with a measure of Trump's vote share. Below, we specify our model with *i* indexing counties and *t* years.

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

[19] Each area corresponds to a pixel in the USDA satellite imagery on crop planting, approximately 22.2 acres—the highest resolution currently available with this technology. The outcome variable is the total count of these pixels in a given county. We chose a quasi-poisson model due to the distribution of the outcome variable, which follows a quasi-poisson distribution. Using one type of spatial unit (e.g., pixel) for analysis may lead to inferential pitfalls due to the modifiable areal unit problem (MAUP) in spatial analysis. Therefore, we check the robustness of the baseline results with a series of spatial lag and spatial error models that are known to mitigate the MAUP. The results presented in **Online Appendix K** indicate the robustness of our baseline results. In addition, we run the baseline models with the ordinary least squares estimator, presented in **Online Appendix L, Table L2** to further confirm the robustness of our results.

[20] We also show that there are no diverging pre-trends in crop planting in Trump counties before the tariff shock in 2018, validating a key assumption of the difference-in-differences analysis as an additional check on our primary findings.

Across these models, we are interested in β_4, the coefficient of the interaction term *Trump Share × Tariff* that 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 and are cross-sectional. As shown in **Table 3**, all models show the expected relationships for β_4. As Trump's vote share increased, counties became more likely to continue planting those goods. These trends are consistent with the estimates in previous OLS models.

	Dependent Variable:					
	Tariffed Count			Soy Count		
	(1)	(2)	(3)	(4)	(5)	(6)
Trump Share (%)	-0.001***	-0.002***	-0.003***	-0.003***	-0.004***	-0.003***
	(0.0004)	(0.0004)	(0.001)	(0.0005)	(0.001)	(0.001)
Tariff	-0.032	-0.012	-0.071	-0.154***	-0.172***	-0.416***
	(0.040)	(0.049)	(0.064)	(0.053)	(0.058)	(0.085)
Trump Share ×	0.002***	0.002**	0.002**	0.003***	0.004***	0.006***
Tariff	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sample	Full	Soy Belt	China	Full	Soy Belt	China
Observations	29,379	12,674	7,671	29,379	12,674	7,671
Controls	Yes	Yes	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 3. Trump Support on Count of Tariff-affected Crop Planting, 2008-2021. This table presents estimates from difference-in-differences analyses using quasi-poisson models. Full regression tables are available in **Online Appendix, Table L**.

5.3 2018 Republican Vote-Share

Next, we perform a test to partially differentiate the competing theoretical mechanisms. Recall that the theory posited that partisan planting resulted from farmers' genuinely held beliefs rather than an expression of support for social reasons. Qualitative evidence from interviews with farmers supported that assertion—farmers were willing to discuss the political situation and disagree amongst themselves, suggesting a lack of social conformity. To further differentiate the two mechanisms, we now test **Hypothesis 2**. If farmers use tariffed crops to express their support to neighbors, their 2018 voting records should also reflect that. In other words, if tariffed crops were a form of expression, voting records should reflect the expressed ideas.

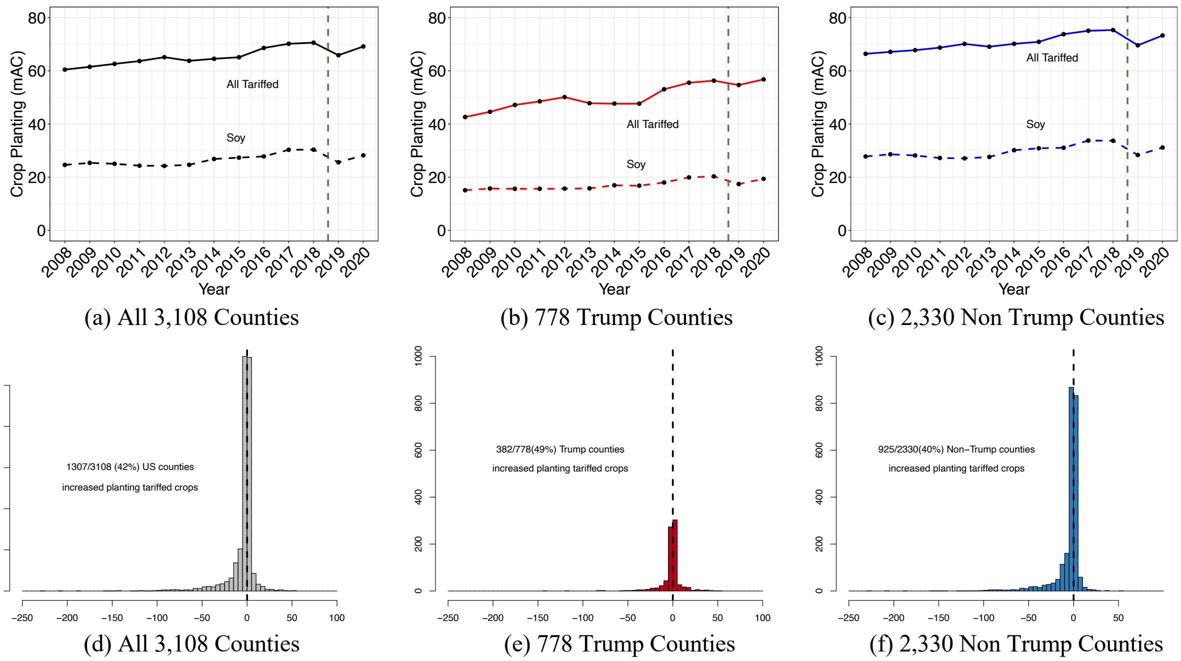
To examine this hypothesis, we re-estimate the main models using the 2018 US House of Representatives voting records as the primary explanatory variable.[21] We expect that farmers' planting decisions relied on their belief in President Trump rather than expressing electoral support for Republicans; thus, we expect the results to be indistinguishable from zero. Indeed, the results in **Table 4** show that county-level support for the Republican party in the 2018 House election is not systematically correlated with farmers' planting decisions in the next year.

	Dependent Variable:					
	Δ Tariffed Acres			Δ Soy Acres		
	(1)	(2)	(3)	(4)	(5)	(6)
Rep. Share 2018 (%)	0.012	-0.019	-0.050	-0.023	-0.034	-0.038
	(0.039)	(0.067)	(0.082)	(0.024)	(0.046)	(0.054)
Sample	Full	Soy B elt	China	Full	SoyBelt	China
Observations	1,085	491	268	1,085	491	268
Controls	Yes	Yes	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.658	0.736	0.815	0.747	0.745	0.720

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

Table 4. Support for the Republican Party in the 2018 US House Election on Tariff-affected Crop Planting. This table presents the ordinary least squares estimates of the effects of support for the Republican Party on changes in tari↲-exposed crop planting using Republican vote shares for the 2018 House election. Models 2 and 5 limit samples to counties in the soy-belt states. Models 3 and 6 limit samples to counties in states whose top exporting country was China in 2017. All models include commuting zone fixed effects. Full results are available in **Online Appendix N, Table N**.

[21] County-level data aggregated from precinct-level election results. Data from the MIT Election Data and Science Lab (2022a,b).



(a) All 3,108 Counties (b) 778 Trump Counties (c) 2,330 Non Trump Counties

(d) All 3,108 Counties (e) 778 Trump Counties (f) 2,330 Non Trump Counties

Figure 4. Trends in Crop Planting exposed to Chinese Tariffs. This figure presents trends in average tariffed crop planting (million acres) between 2008 and 2020 and changes in tariffed planting (thousand acres) in 2019 by Trump's vote share. In Panels (a) to (c), solid lines indicate the average planting volume of crops exposed to the 2018 Chinese tariffs. The dashed lines indicate the average planting volume of soybeans. 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 three quartiles (74.9%) vote share in the 2016 presidential election. Panels (c) and (f) indicate results for non-Trump counties with a vote share below three quartiles.

Looking back at the original puzzle introduced in **Figure 1**, a disaggregation of political 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 tariff-exposed goods sharply decreased overall. However, Panel (b) limits the data to counties whose 2016 Trump vote-share fell into the top 25th percentile. These counties exhibit a much lower, if any, drop in the 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 more substantial in non-Trump counties (counties whose vote share fell in the bottom 75th percentile). Only 42% of these counties increased their total planting levels. Most of the 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. Agriculture was not the only industry affected by President Trump's 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 our analyses, it should be possible to find evidence for these same mechanisms in various sectors.

In fact, if anything, the agricultural industry creates a hard test for the theory. The local signaling mechanism is weak in the agricultural industry, 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 labor and customers decreases the incentives for firms to behave ideologically. Also, large farms often find it difficult to quickly switch crops, often preferring to plan to plant 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 specific products. But it was also 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 the origins of trade preferences suggests that information is one of the most significant barriers blocking individuals from following their pocketbook (Rho and Tomz 2017). Heuristics are more important and more challenging to gather accurate information. Therefore, if these findings hold in very high-information contexts, 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, business leaders may 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 et al. 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 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 also amplify itself in firm behavior.

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