Bean Counters: The Effect of Soy Tariffs on Change in Republican Vote Share between the 2016 and 2018 Elections

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Abstract

How do trade wars affect voting for the President's party? President Trump's aggressive tariffs on China, despite his largely rural electoral support base, provide a unique opportunity to analyze the relationship between international trade policy and domestic support. If trade-related considerations were ever decisive to American voters, the stark decrease in soy prices, a direct effect of Trump-initiated tariffs immediately preceding the 2018 midterm election, serves as a critical test for studying their effect. This letter shows a robust inverse relationship between county-level soybean production and the change in Republican vote share between the 2016 and 2018 congressional elections.

Key Words: trade wars, tariffs, China, vote share, agriculture

Running Head: Soy Tariffs and U.S. Voting Patterns, 2016–2018

Supplementary materials are available in an online appendix. Replication files are available in the JOP Data Archive on Dataverse (http://thedata.harvard.edu/dvn/dv/jop).

President Donald Trump shook up trade policy, otherwise typically little-watched by the public, with several aggressive tariff actions (Noland, 2018). This, in turn, provoked retaliation, notably by China (Li, Zhang and Hart, 2018; Liu and Woo, 2018), whose trade barriers targeted President Trump's rural-skewing support base (Monnat and Brown, 2017). China's tariffs particularly threatened the soybean sector, which comprised roughly two thirds of American agricultural exports to China. As the world's largest soybean importer, China had considerable power in soybean markets (Taheripour and Tyner, 2018). This market power directly reached American farmers, as China in 2016 imported $14 billion of American soybeans, over a third of the year's total production of $41 billion. Unsurprisingly, upon imposition of Chinese tariffs, American soybean prices fell rapidly; the cost of a bushel of soybeans had hovered within a few cents of $10.25 for most of spring 2018 but fell by over a dollar in June as tariffs bit, ultimately reaching a ten-year low in September during the fall harvest. Even after some recovery, the price remained around $9.00 at the end of 2018. Soybean producers' revenue thus fell by over 10% from what might have been anticipated during the planting season, with profits falling concomitantly further.

Nor was the soybean sector a trivial economic interest: soybeans were the United States' second most valuable crop (behind maize), and output had, spurred by surging Chinese demand, increased dramatically in recent years (USDA, 2018). Moreover, this trade conflict's costs would affect not just soybean producers themselves but also whole communities, as soybean farmers' reduced income affected sales of local service providers and even asset values of neighboring homeowners (Scheve and Slaughter, 2001). While Secretary of Agriculture Sonny Perdue announced a multibillion-dollar bailout to ameliorate the trade war's effect on farmers, relatively few of these funds were disbursed promptly, and the effort was perceived as not nearly covering farmers' losses (Rappeport, 2018).

Voters in soybean-producing areas thus had unusually stark impetus to pay attention to, and make electoral decisions because of, trade policy. Indeed, support for Trump and his Republican Party marks a critical test of the relevance of international political economy to American voters: with a clear shift in market conditions widely attributed to American trade-policy choices, trade policy had unparalleled visibility and importance. If trade-related considerations were ever pivotal in Americans' decisions of whether and for whom to vote, November 2018's general election in soybean country would be the context.

To determine whether voters punish the incumbent President's party for economically consequential international-trade policies, we model the change in the Republican vote share between the 2016 and 2018 elections to the House of Representatives as a function of county-level soy production. We find strong evidence that voters hold the president's party accountable for trade policies. Counties heavily reliant on soy production shifted against the Republican Party by as much as 20 percentage points more than we would otherwise expect.

Trade Policy and Voting Behavior

Our central research question asks how trade wars affect support for incumbent political parties. In the United States, trade's economic costs have translated to electoral penalties for incumbents in two ways. First, locales most disadvantaged by free trade may increase support for Democrats, who favor worker compensation and other redistributive policies (Che et al., 2016). Alternatively, trade-induced losses may spark economic nationalism—a protectionist sentiment blaming domestic economic misfortunes on out-groups (e.g., foreigners). Research has observed both electoral responses to trade shocks: Autor et al. (2017) finds voters in ethnically diverse districts responding to economic shocks by supporting politicians that advocate for worker compensation policies, while districts with majority non-Hispanic white populations react by increasing support for right-wing, protectionist candidates. Margalit (2011) finds that, while job losses generally cost incumbents votes, this effect doubles in size when offshoring, not other factors such as domestic competition, caused the job loss (also see Jensen, Quinn and Weymouth, 2017; Kleinberg and Fordham, 2013).

While most past research examined backlash against free trade and globalization, the election of Donald Trump set up a critical test of the reverse effect: whether voters also punish politicians for adverse economic effects of protectionism. Elected on an economically protectionist platform, Trump quickly delivered the promised tariffs against China, which were promptly reciprocated by Chinese tariffs against US-produced soy—a production staple of Trump's agricultural support base. The sharp decrease in demand for soybeans led to a substantial price drop, economically imperilling soybean farmers and their communities. Sections of Trump's rural base thus had unusually strong cause to infer a direct link between trade policy and their personal well-being. This strong policy salience is, however, countered not only by the low baseline lack of interest in foreign affairs but also by intense partisan polarization (Abramowitz and Webster, 2016; Gelman et al., 2016). In addition, the separation of power between Congress and the President—with the latter not facing reelection until 2020—may have diluted the clarity of responsibility and tempered soybean communities' ability to hold policy-makers accountable in the 2018 elections (Hellwig and Samuels, 2008). This letter aims to use data on the change in the county-level Republican vote share between the 2016 and 2018 congressional elections to test whether locales highly reliant on soy production saw shrinking support for the Republican Party.[1]

Research Design

The dependent variable is the change in Republican vote share between the 2016 and 2018 general elections to the House of Representatives, Δ*Republican Votes*, measured as the difference in Republican vote share out of the two-party vote, i.e. $\frac{Rep\ 2018}{Rep\ 2018+Dem\ 2018} - \frac{Rep\ 2016}{Rep\ 2016+Dem\ 2016}$. To construct the measure, we assembled county-level vote totals for the two major parties in the 2016 and 2018 general elections for US Representative. We excluded Alaska (for which county-equivalent units are not consistently defined) and counties where elections were not contested in both election years, since some states do not report votes for

[1]With the President not on the ballot in the midterm, we opt for comparing votes for the US Representatives, arguing that a change in the Republican Party's share of the House vote reflects, in part, voters' reaction to the tariffs and their consequences. Although a vote for the Republican Party is obviously not the same as a vote for Trump, in recent elections, voters have demonstrated an increasing tendency to vote for the same party for both Congressional and Presidential elections. Votes for Congresspeople increasingly reflect views of parties rather than views about specific candidates (Jacobson, 2015; Fiorina, 2017; Sievert and McKee, 2018).

uncontested races.[2] The resulting sample includes 2414 counties from 49 states.

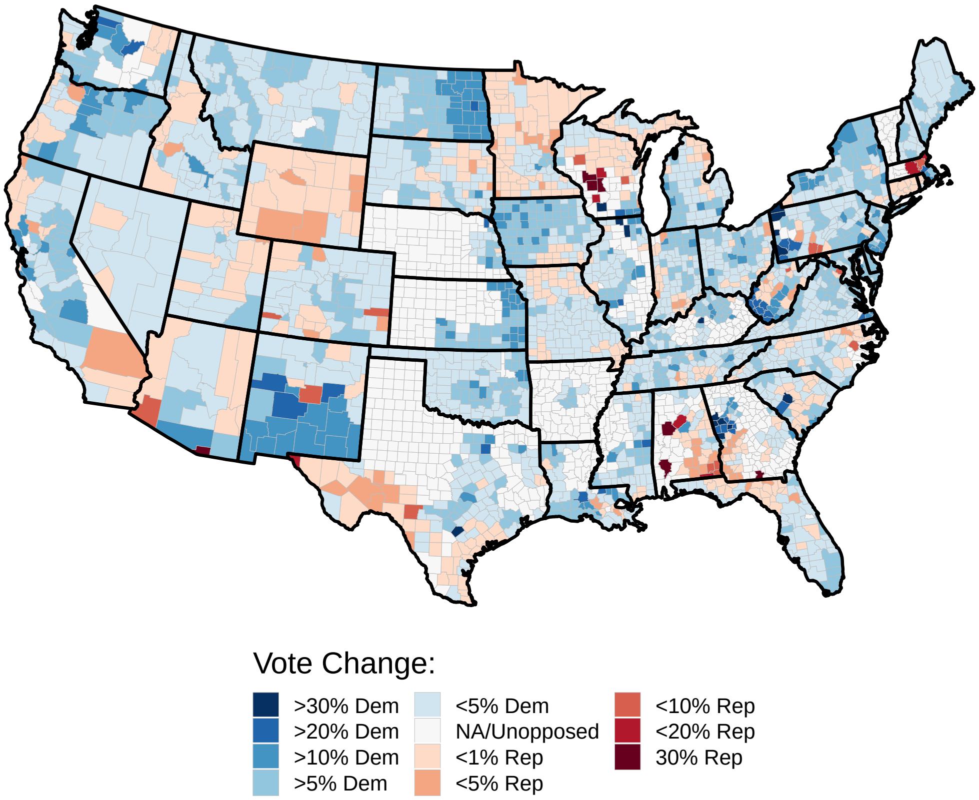
Figure 1 shows the spatial distribution of the dependent variable. The prevalence of blue accords with pundits' "blue wave" trope describing widespread electoral gains by Democrats. The map colors, of course, solely indicate changes in vote share between the two elections, not actual electoral outcomes. For example, North Dakota elected a Republican to the US House of Representatives in both 2016 and 2018, albeit with a narrower margin in all but one county. In 2016, in an average North Dakota county, the Republican candidate gained about 78 percent of the vote share, while the corresponding number in 2018 was 69 percent—a 9 percentage-point decrease. As some initial evidence of voters punishing the incumbent party for trade policies, large areas of voter shifts against the Republicans appear in the rural Midwest and along the Missouri and the Mississippi rivers—hotbeds of soy production.

The key independent variable is a county's economic reliance on soybean output. For robustness, we measure this in two ways: in millions of bushels and in dollar sales. Both measures use 2012 US Department of Agriculture (USDA) figures and are log-normalized in the statistical analysis.

We control for several factors influential for vote choice and turnout: county-level GDP/capita (in USD, logged) and its square, unemployment rate, education, urbanization, percent of black and other racial minorities, percent of Hispanic/Latino population, percent foreign population, and the Republican percent of the two-party vote in the 2016 election. To account for district-level effects, such as the incumbency advantage and district's ideological lean, we also estimate a second model only on the counties that lie wholly within a single congressional district. Data on county-level economic outcomes came from the Bureau of Economic Analysis, while demographic variables are from the most recent US Census American Community Survey (2013–2017 averages). We measure educational attainment using two variables: percent of the adult popuation with at least a high-school degree (variable

[2]Reported results include results from Pennsylvania, which redrew Congressional-district boundaries between 2016 and 2018. Omitting redistricted counties from the dataset does not substantially change results.

Figure 1: Change in Vote Share Between the 2016 and 2018 Congressional Elections



High School), and percent with at least a Bachelor's degree, *Bachelor's*. Δ*Incumbency* is the change from 2016 to 2018 of a variable equal to 1 if an incumbent Democrat ran for the House in the respective election, -1 if an incumbent Republican did, and 0 otherwise. *District Ideology* is the Cook Political Report's Partisan Voting Index as of 2015: how many percentage points more Republican the district had voted in recent presidential elections than did the country as a whole. We test our hypotheses by estimating a multi-level ordinary least squares regression with counties (level 1) nested within states (level 2) (Gelman and Hill, 2007, 263).

Results

Table 1 presents the resulting statistical analysis. The first two models include the full sample, while models 3–4 include only counties that are not split between congressional

Table 1: Change in Republican Vote Share Between 2016 and 2018 Elections as a Function of Soy Output

	All counties				*Single-District Counties*			
Soy Production	-1.26*	(0.29)			-1.27*	(0.28)		
Soy Sales			-4.00*	(0.97)			-3.85*	(0.91)
GDP/cap., logged	0.62*	(0.30)	0.62*	(0.30)	0.23	(0.32)	0.22	(0.32)
(GDP/cap., logged)^2	-0.25	(0.27)	-0.22	(0.27)	0.13	(0.34)	0.19	(0.34)
Unemployment	-0.01	(0.02)	0.01	(0.02)	-0.01	(0.03)	0.01	(0.03)
High-school Diploma	0.17*	(0.04)	0.17*	(0.04)	0.19*	(0.04)	0.19*	(0.04)
Bachelor's Degree	-0.15*	(0.04)	-0.15*	(0.04)	-0.06	(0.05)	-0.05	(0.05)
Urbanization	-2.24*	(0.50)	-2.21*	(0.50)	-2.60*	(0.61)	-2.58*	(0.61)
Black, logged	-0.62*	(0.17)	-0.66*	(0.17)	-0.23	(0.18)	-0.28	(0.18)
Other Non-White, logged	-0.98*	(0.25)	-0.96*	(0.25)	-0.59*	(0.26)	-0.56*	(0.26)
Latino, logged	0.08	(0.29)	0.06	(0.29)	0.43	(0.33)	0.41	(0.33)
Foreign, logged	0.33	(0.21)	0.34	(0.21)	0.34	(0.21)	0.34	(0.21)
Rep 2016 Vote	-0.18*	(0.01)	-0.18*	(0.01)	-0.10*	(0.01)	-0.10*	(0.01)
ΔIncumbent					1.62*	(0.29)	1.63*	(0.29)
Dist. Ideology					-0.12*	(0.02)	-0.12*	(0.02)
Constant	-3.56*	(0.46)	-3.56*	(0.46)	-4.11*	(0.61)	-4.11*	(0.60)
Variance:								
States	8.69		8.77		10.23		10.19	
County	28.72		28.74		20.68		20.73	
Observations:								
County	2414		2414		1534		1534	
States	49		49		31		31	

Notes: $^*p<.05$, $^\dagger p<0.1$ (two-tailed). State-level random effects are not shown.

districts. In models 1 and 3, soy reliance is measured in millions of bushels; models 2 and 4 measure soy reliance in terms of soy sales (in thousands USD).

As predicted, *Soy Production* has negative and statistically significant effect in all model specifications. This indicates a direct relationship between county economic reliance on soy production and *decrease* in Republican vote share between the 2016 and the 2018 congressional elections, while holding all other variables constant.[3] This effect is substantively large: an average rural county with soy production of 10,000 bushels shifted against the Republican party by as much as 14 percent—about 11 percentage points more than a comparable county with no soy production (see the Online Appendix's Figure 3).[4]

[3]This result is robust to a variety of specifications and model choices. See Online Appendix.

[4]Ten thousand bushels is typical output for a county with just a handful of soy farms.

Control variables are in expected directions. Republican vote share decreased less where relatively fewer people had college education and where Republicans gained incumbency advantage, as measured by our $\Delta Incumbent$ variable. In contrast, more-urban and racially diverse counties saw relatively larger decreases in Republican vote share between the two elections. *Rep 2016 Vote* is negative and statistically significant, consistent with the usual midterm-election depression in turnout from the President's supporters, satisfied with the status quo, compared to the opposition (Tufte, 1975; Campbell, 2015). Finally, *District Ideology* is negative in the last two models, in line with accounts that Trumpism's rise caused previously Republican-leaning areas such as suburbs to drift away from their previous partisan alignment (Campbell, 2018).

Conclusion

In studies of international political economy, the public often appears marginally sensitive at best to trade policy; when concern for trade does appear, it can reflect identity cues as much as personal pocketbook issues. However, in exploring the effects of one particularly dramatic shift in trade policy, the United States—China trade war of 2017–2018 and its sudden imposition of restrictions on American soybean exports—the above analysis finds strong effects. Localities dependent on soybean production that thus suffered most from the trade confrontation tended to see relatively large shifts against voting for the incumbent President's party. This result is particularly notable since most previous studies of trade-policy preferences have found larger public responses to open trade policy, rather than to the protectionist, higher-barrier policy examined here. It is further noteworthy that the result emerges in the contemporary United States, where fervent and polarized partisan identities might be expected to reduce the scope for detectable effects: notwithstanding the Trump coalition's reputation for unshakable loyalty, the president's party still appears to face electoral costs from trade-policy choices. Even if public-opinion polling suggests few voters have deeply considered trade-policy preferences, they may respond when confronted with changes in trade policy itself. Such changes' economic ramifications may matter independently of stated ideological attitudes about trade.

Future research should complement this finding with individual-level analysis to better examine who, exactly, responded to the change in trade policy. Was the effect concentrated among farmers themselves, or did it extend to other locals? And did those who change their voting behavior actually switch parties, or simply become less likely to turn out to vote for their partisan preference? It is also worth exploring responses to the ongoing trade conflict in other countries and industries. While the context of American agriculture is *sui generis*, the potential for governments to suffer electoral costs from trade wars may be expanding amidst surging populism in many countries.

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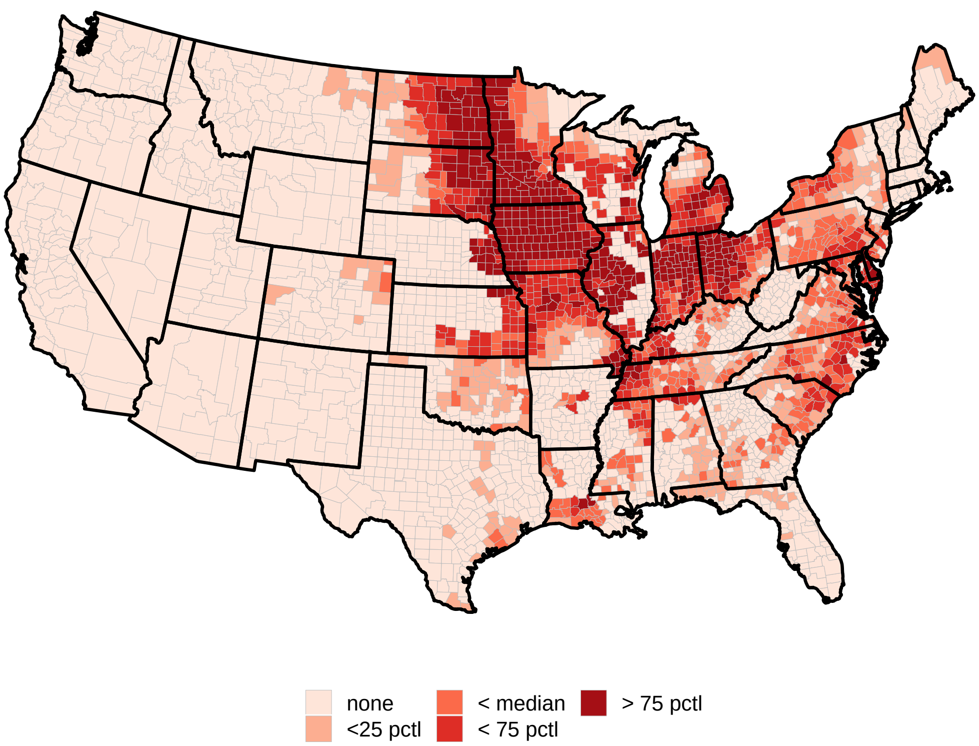
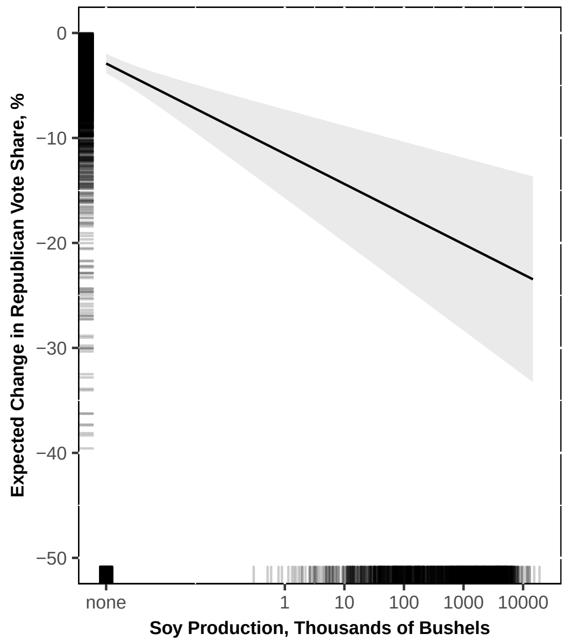
Online Appendix

Figure 2: 2012 Soy Production (bushels)



Note: Data obtained from the USDA.

Figure 3: Expected Change in Vote Share of the Two Major Parties as a Function of Soy Production



Note: All control variables are set to the values of an average rural county. Estimates obtained using coefficient from Model 1. Rug plots show the (jittered) distributions of the actual data.

Robustness Checks

In what follows we provides a series of robustness checks for the models presented in Table 1. These include models with state- and district-level fixed effects, models that account for production of alternative crops (corn and cotton), a model that controls for Trump's 2016 margin, models that account for spatial interdepedence in vote and soy production, models that implement a matched design, a model that implements a difference-in-difference design, and a model that uses the 2017 USDA data on soy production. Our main results are robust to all these specifications.

State- and District-Level Fixed Effects

The models in Table 1 were estimated using a multi-level model that allows for varying intercepts among states (random effects) (Gelman and Hill, 2007, 244). As a robustness check, we also estimated three additional models with fixed effects. Table 2 shows the results for all models re-estimated with state-level fixed effects rather than the random effects, Table 3 shows the results with district-level fixed effects, and Table 4 shows the results with two-way (state and district) fixed effects.[5] The results remain consistent with those in Table 1 in all specifications.

[5] Of course, for single-district states, the fixed effect represents both the state and the district. Since fixed effects are simply binary indicator variables, we were able to construct fixed effects for counties that are split among multiple districts as well, which admittedly makes Models 3 and 4 less relevant. We include Models 3 and 4 for completeness.

Table 2: Change in Republican Vote Share Between 2016 and 2018 Elections as a Function of Soy Production, with State-Level Fixed Effects

	All counties				*Single-District Counties*			
Soy Production	-1.21*	(0.30)			-1.29*	(0.29)		
Soy Sales			-3.84*	(1.00)			-3.88*	(0.93)
GDP/cap., logged	0.65*	(0.30)	0.65*	(0.30)	0.27	(0.32)	0.27	(0.32)
(GDP/cap., logged)^2	-0.28	(0.27)	-0.24	(0.27)	0.12	(0.34)	0.18	(0.34)
Unemployment	-0.01	(0.02)	0.01	(0.02)	0.01	(0.03)	0.01	(0.03)
High-school Diploma	0.19*	(0.04)	0.18*	(0.04)	0.21*	(0.04)	0.21*	(0.04)
Bachelor's Degree	-0.14*	(0.04)	-0.14*	(0.04)	-0.04	(0.05)	-0.04	(0.05)
Urbanization	-2.12*	(0.50)	-2.09*	(0.50)	-2.46*	(0.61)	-2.43*	(0.61)
Black, logged	-0.66*	(0.18)	-0.70*	(0.18)	-0.25	(0.19)	-0.30	(0.19)
Other Non-White, logged	-0.98*	(0.25)	-0.95*	(0.25)	-0.60*	(0.26)	-0.57*	(0.26)
Latino, logged	-0.01	(0.31)	-0.03	(0.31)	0.41	(0.33)	0.38	(0.33)
Foreign, logged	0.38	(0.22)	0.38	(0.22)	0.38	(0.21)	0.38	(0.22)
Rep 2016 Vote	-0.18*	(0.01)	-0.18*	(0.01)	-0.09*	(0.01)	-0.09*	(0.01)
ΔIncumbent					1.66*	(0.29)	1.66*	(0.29)
Dist. Ideology					-0.14*	(0.02)	-0.14*	(0.02)
Constant	4.26*	(0.92)	4.36*	(0.91)	3.45*	(0.91)	3.64*	(0.91)
Observations:								
County	2414		2414		1534		1534	
States	49		49		31		31	

Notes: *$p < .05$ (two-tailed). State-level fixed effects are not shown.

Table 3: Change in Republican Vote Share Between 2016 and 2018 Elections as a Function of Soy Production, with District-Level Fixed Effects

	All counties				*Single-District Counties*			
Soy Production	-0.83*	(0.24)			-0.85*	(0.22)		
Soy Sales			-2.07*	(0.76)			-2.38*	(0.69)
GDP/cap., logged	0.28	(0.21)	0.27	(0.21)	0.03	(0.21)	0.01	(0.22)
$(\text{GDP/cap., logged})^2$	0.10	(0.19)	0.14	(0.19)	0.57*	(0.23)	0.61*	(0.22)
Unemployment	0.01	(0.02)	0.01	(0.02)	-0.02	(0.02)	-0.02	(0.02)
High-school Diploma	0.09*	(0.03)	0.09*	(0.03)	0.14*	(0.03)	0.14*	(0.03)
Bachelor's Degree	-0.14*	(0.03)	-0.14*	(0.03)	-0.08*	(0.04)	-0.08*	(0.04)
Urbanization	-1.72*	(0.38)	-1.70*	(0.38)	-2.26*	(0.43)	-2.25*	(0.43)
Black, logged	-0.22	(0.14)	-0.24	(0.14)	0.05	(0.15)	0.03	(0.15)
Other Non-White, logged	-0.60*	(0.17)	-0.57*	(0.17)	-0.43*	(0.18)	-0.40*	(0.18)
Latino, logged	0.04	(0.22)	0.04	(0.22)	0.36	(0.24)	0.35	(0.24)
Foreign, logged	0.23	(0.14)	0.23	(0.14)	0.14	(0.14)	0.13	(0.14)
Rep 2016 Vote	-0.05*	(0.01)	-0.05*	(0.01)	-0.03*	(0.01)	-0.03*	(0.01)
ΔIncumbent					-29.83*	(3.83)	-29.85*	(3.84)
Dist. Ideology					0.31*	(0.10)	0.30*	(0.10)
Constant	-3.14*	(0.35)	-3.15*	(0.35)	-31.16*	(3.85)	-31.30	(3.85)
Observations:								
County	2414		2414		1534		1534	
States	49		49		31		31	

Notes: *p <.05, †p <0.1 (two-tailed). District-level fixed effects are not shown.

Table 4: Change in Republican Vote Share Between 2016 and 2018 Elections as a Function of Soy Production, with State- and District-Level Fixed Effects

	All counties				*Single-District Counties*			
Soy Production	-0.81*	(0.24)			-0.85*	(0.22)		
Soy Sales			-2.03*	(0.77)			-2.38*	(0.69)
GDP/cap., logged	0.24	(0.20)	0.23	(0.20)	0.03	(0.21)	0.01	(0.22)
(GDP/cap., logged)^2	0.17	(0.19)	0.20	(0.19)	0.57*	(0.23)	0.61*	(0.22)
Unemployment	0.01	(0.02)	0.01	(0.02)	-0.02	(0.02)	-0.02	(0.02)
High-school Diploma	0.10*	(0.03)	0.10*	(0.03)	0.14*	(0.03)	0.14*	(0.03)
Bachelor's Degree	-0.13*	(0.03)	-0.13*	(0.03)	-0.08*	(0.04)	-0.08*	(0.04)
Urbanization	-1.64*	(0.38)	-1.61*	(0.38)	-2.26*	(0.43)	-2.25*	(0.43)
Black, logged	-0.11	(0.15)	-0.13	(0.15)	0.05	(0.15)	0.03	(0.15)
Other Non-White, logged	-0.62*	(0.17)	-0.60*	(0.17)	-0.43*	(0.18)	-0.40*	(0.18)
Latino, logged	-0.03	(0.22)	-0.04	(0.22)	0.36	(0.24)	0.35	(0.24)
Foreign, logged	0.23	(0.14)	0.23	(0.14)	0.14	(0.14)	0.13	(0.14)
Rep 2016 Vote	-0.04*	(0.01)	-0.04*	(0.01)	-0.03*	(0.01)	-0.03*	(0.01)
ΔIncumbent					-5.68*	(2.63)	7.23*	(2.08)
Dist. Ideology					1.15*	(0.12)	30.04*	(3.38)
Constant	16.54*	(2.70)	16.73*	(2.70)	-11.44*	(1.70)	-11.54*	(1.71)
<u>Observations:</u>								
County	2414		2414		1534		1534	
States	49		49		31		31	

Notes: $^*p$ <.05, $^\dagger p$ <0.1 (two-tailed). State- and district-level fixed effects are not shown.

Corn and Cotton Counties

As an additional robustness test, we checked for a possible effect in corn- and cotton-producing counties. Like soy, corn and cotton prices experienced price declines in the summer of 2018, although these declines are less directly attributable to Chinese exports, which are modest for the latter two commodities. Per USDA reports, particularly the Foreign Agriculture Trade of the United States (FATUS) data, corn exports to China were 0.3% or less of total corn-production value in every year from 2015 to 2017. Most cotton production, meanwhile, was already subject to a 40% tariff for import in China, which capped American reliance on the Chinese export market: China's adding 25 percentage points further of retaliatory tariff was much less important than was adding that surcharge to the previous 3 percent tariff on soy. The decline of cotton prices in the summer of 2018 also followed a major price rally over the previous year, so that even after the summer declines prices were roughly where they had been during the planting season, and higher than they had been during the 2016 or 2017 harvests. Maize production thereby serves as a placebo test of the effect of trade wars, while cotton production reflects a market that had somewhat greater exposure to Chinese exports but where immediate price signals did not provide the same impetus for punishing the incumbent President's party.

The data for corn and cotton production and sales were obtained from the USDA website.[6] The correlation between *Soy Production* and *Corn Production* is 0.91, the correlation between *Soy Sales* and *Corn Sales* is only about 0.61. The correlation between soy and cotton production is -0.05, and -0.09 for the sales measures. The results presented in Table 5 show that including these variables does not change the effect of the soy variables, which are still negative and statistically significant. The corn variables are not statistically significant in any specifications, while both of the coefficients on the cotton measures are positive and statistically significant. This indicates that, while the support for the Republican Party

[6]For corn production, USDA reports the number of bushels of corn as grain, but not silage. For sales, USDA reports the aggregate sales of grain and silage.

decreased in soy counties, it grew even stronger in cotton counties.

The difference between the results for cotton and soybeans offers intriguing though not definitive hints about potential mechanisms underpinning the main text's results. Even though the tit-for-tat trade restrictions limited cotton producers' access to the Chinese market, the electoral consequences look strikingly different from those on soybean producers'. This suggests that the driving factor behind the main text's result is not that tariffs were simply ideologically unacceptable to farm-country voters or that people punished (Republican) incumbents for perceived losses from prices falling from some absolute recent peak in prices. Soybeans' more-dramatic price shift, especially vis-à-vis expected prices at the time of planting or previous years' expectations, may have produced qualitatively different effects. Another possibility is that the differing structures of federal-government emergency assistance to farmers of different commodities proved more satisfying to cotton interests than to soybean producers.

Table 5: Change in Republican Vote Share Between 2016 and 2018 Elections as a Function of Soy Production, Accounting for Corn and Cotton Production

	All counties				*Single-District Counties*			
Soy Production	-1.78*	(0.50)			-1.38*	(0.51)		
Soy Sales			-4.79*	(1.02)			-4.34*	(0.97)
Corn Production	0.31	(0.31)			-0.03	(0.34)		
Corn Sales			0.06	(0.04)			0.03	(0.05)
Cotton Production	1.13*	(0.28)			1.55*	(0.29)		
Cotton Sales			0.20*	(0.05)			0.26*	(0.05)
GDP/cap., logged	0.63*	(0.29)	0.68*	(0.29)	0.21	(0.32)	0.27	(0.32)
$(\text{GDP/cap., logged})^2$	-0.20	(0.27)	-0.14	(0.27)	0.27	(0.34)	0.36	(0.34)
Unemployment	0.01	(0.02)	0.02	(0.02)	0.01	(0.03)	0.01	(0.03)
High-school Diploma	0.18*	(0.04)	0.17*	(0.04)	0.20*	(0.04)	0.19*	(0.04)
Bachelor's Degree	-0.12*	(0.04)	-0.12*	(0.04)	-0.04	(0.05)	-0.05	(0.05)
Urbanization	-2.18*	(0.49)	-2.05*	(0.49)	-2.48*	(0.61)	-2.34*	(0.60)
Black, logged	-0.74*	(0.17)	-0.84*	(0.17)	-0.42*	(0.18)	-0.48*	(0.18)
Other Non-White, logged	-0.90*	(0.25)	-0.89*	(0.25)	-0.50†	(0.26)	-0.50†	(0.26)
Latino, logged	-0.06	(0.30)	-0.03	(0.29)	0.23	(0.33)	0.25	(0.32)
Foreign, logged	0.39	(0.21)	0.37	(0.21)	0.44*	(0.21)	0.38†	(0.21)
Rep 2016 Vote	-0.18*	(0.01)	-0.18*	(0.01)	-0.09*	(0.01)	-0.09*	(0.01)
ΔIncumbent					1.47*	(0.29)	1.50*	(0.28)
Dist. Ideology					-0.11*	(0.02)	-0.11*	(0.02)
Constant	-3.58*	(0.45)	-3.57*	(0.46)	-4.10*	(0.59)	-4.11*	(0.58)
Variance:								
States	8.48		8.67		9.50		9.34	
County	28.54		28.32		20.35		20.05	
Observations:								
County	2414		2414		1534		1534	
States	49		49		31		31	

Notes: $^*p < .05$, $^\dagger p < 0.1$ (two-tailed). State-level random effects are not shown.

Controlling for Trump's 2016 Margin

Although the models of Table 1 control for the Republican 2016 vote, it is also possible that the difference in the support for the Republican party had to do with the difference between a Presidential election and a midterm election. To check for this, we re-estimated our models, substituting *Rep 2016 Vote* with *Trump's 2016 Margin*.[7] The results are presented in Table 6. The main results are unchanged, but the coefficient on *Trump's 2016 Margin* flips signs between the full sample and the sub-sample of counties that are not split between districts. We have no good explanation for this result, though it presumably stems from some distinctive features of counties that are not split between districts.

[7] These two variables are correlated at 0.9.

Table 6: Change in Republican Vote Share Between 2016 and 2018 Elections as a Function of Soy Production, Controlling for Trump's 2016 Margin

	All counties				*Single-District Counties*			
Soy Production	-1.37*	(0.31)			-1.12*	(0.28)		
Soy Sales			-4.16*	(1.04)			-3.19*	(0.93)
GDP/cap. (logged)	0.62†	(0.32)	0.61†	(0.32)	0.15	(0.33)	0.14	(0.33)
$(\text{GDP/cap.})^2$ (logged)	0.09	(0.29)	0.13	(0.29)	0.16	(0.35)	0.22	(0.35)
Unemployment	0.02	(0.03)	0.03	(0.03)	0.03	(0.03)	0.04	(0.03)
High-school Diploma	0.11*	(0.04)	0.11*	(0.04)	0.13*	(0.04)	0.13*	(0.04)
Bachelor's Degree	-0.13*	(0.05)	-0.13*	(0.05)	-0.06	(0.05)	-0.06	(0.05)
Urbanization	-1.64*	(0.53)	-1.60*	(0.53)	-2.05*	(0.62)	-2.01*	(0.62)
Black (logged)	0.07	(0.19)	0.03	(0.19)	0.30	(0.19)	0.25	(0.19)
Other Non-White (logged)	-0.23	(0.27)	-0.20	(0.27)	-0.13	(0.26)	-0.09	(0.26)
Latino (logged)	0.39	(0.32)	0.38	(0.32)	0.53	(0.33)	0.51	(0.33)
Foreign (logged)	0.13	(0.23)	0.14	(0.23)	0.22	(0.22)	0.21	(0.22)
Trump's 2016 Margin	-1.39*	(0.62)	-1.39*	(0.62)	2.87*	(0.75)	2.88*	(0.75)
ΔIncumbent					1.61*	(0.29)	1.62*	(0.29)
Dist. Ideology					-0.25*	(0.02)	-0.25*	(0.02)
Constant	-3.40*	(0.48)	-3.39*	(0.48)	-4.14*	(0.65)	-4.14*	(0.65)
Variance:								
States	9.47		9.54		11.78		11.75	
County	33.16		33.20		21.15		21.21	
Observations:								
County	2414		2414		1534		1534	
States	49		49		31		31	

Notes: $^*p <.05$, $^\dagger p <0.1$ (two-tailed). State-level random effects are not shown.

Spatial Dependence

In order to rule out the confounding effects of spatial dependence in the data, we estimated three additional sets of models: (1) models that account for the spatial dependence in the distribution of soy bean production (a spatial X model) (2) models that account for spatial dependence in vote (a spatial Y model), (3) and models that account for spatial dependence in the error term. We defined spatial connectivity in terms of direct geographical contiguity: two counties are considered as spatially dependent if they share a land border. The result is a $N \times N$ contiguity matrix, with zeroes on the major diagonal and other cell entries coded as one if the corresponding two counties are contiguous and zero otherwise.

For the purposes of the spatial X model, we calculated the average soy production in neighboring counties by pre-multiplying the contiguity matrix by the transpose of the vector that contains the independent variable (*Logged Soy Production* or *Logged Soy Sales*, depending on the model). Finally, we re-estimated the four models, including this new variable as a control. The results are presented in Table 7.

The spatial Y and spatial error models were estimated following Franzese and Hays (2007, 2008) using the `spatialreg` version in `R`. The results of these models are presented in Tables 8 and 9, accordingly. The spatial Y model models the correlation in the outcome variable via a ρ parameter, while the spatial error model estimates an error-dependence parameter λ. The coefficients on our main variables are robust to these specification tests, though the coefficients on *Soy Sales* in the spatial X and error models are singnificant only at $p < 0.1$ (one-tailed).

Table 7: Change in Republican Vote Share Between 2016 and 2018 Elections as a Function of Soy Production, Accounting for Spatial Dependence in Soy Production

	All counties				*Single-District Counties*			
Soy Production	-1.03*	(0.39)			-0.85*	(0.38)		
Soy Sales			-2.51*	(1.29)			-1.85‡	(1.22)
Neighbors' Production	-0.26	(0.30)			-0.45‡	(0.29)		
Neighbors' Sales			-1.81†	(1.03)			-2.41*	(0.97)
GDP/cap., logged	0.62*	(0.30)	0.63*	(0.30)	0.22	(0.32)	0.21	(0.32)
(GDP/cap., logged)^2	-0.25	(0.27)	-0.22	(0.27)	0.13	(0.34)	0.18	(0.34)
Unemployment	-0.01	(0.02)	-0.01	(0.02)	-0.01	(0.03)	0.01	(0.03)
High-school Diploma	0.17*	(0.04)	0.17*	(0.04)	0.19*	(0.04)	0.19*	(0.04)
Bachelor's Degree	-0.15*	(0.04)	-0.15*	(0.04)	-0.06	(0.05)	-0.06	(0.05)
Urbanization	-2.23*	(0.50)	-2.18*	(0.50)	-2.56*	(0.61)	-2.52*	(0.61)
Black, logged	-0.62*	(0.17)	-0.66*	(0.17)	-0.24‡	(0.18)	-0.28‡	(0.18)
Other Non-White, logged	-0.99*	(0.25)	-0.98*	(0.25)	-0.61*	(0.26)	-0.60*	(0.26)
Latino, logged	0.07	(0.29)	0.06	(0.29)	0.43‡	(0.33)	0.43‡	(0.33)
Foreign, logged	0.34‡	(0.21)	0.35‡	(0.21)	0.34‡	(0.21)	0.35‡	(0.21)
Rep 2016 Vote	-0.18*	(0.01)	-0.18*	(0.01)	-0.10*	(0.01)	-0.10*	(0.01)
ΔIncumbent					1.64*	(0.29)	1.65*	(0.29)
Dist. Ideology					-0.12*	(0.02)	-0.12*	(0.02)
Constant	-3.56*	(0.46)	-3.56*	(0.46)	-4.01*	(0.61)	-3.98*	(0.61)
Variance:								
States	8.68		8.75		10.24		10.18	
County	28.73		28.71		20.66		20.66	
Observations:								
County	2414		2414		1534		1534	
States	49		49		31		31	

Notes: $^*p$ <.05, $^†p$ <0.1 (two-tailed); $^‡p$ <0.1 (one-tailed). State-level random effects are not shown.

Table 8: Change in Republican Vote Share Between 2016 and 2018 Elections as a Function of Soy Production, Accounting for Spatial Dependence in Vote

	All counties			
Soy Production	-0.82*	(0.27)		
Soy Sales			-2.45*	(0.89)
GDP/cap., logged	0.36	(0.27)	0.36	(0.27)
(GDP/cap., logged)^2	-0.17	(0.24)	-0.15	(0.24)
Unemployment	-0.01	(0.02)	-0.01	(0.02)
High-school Diploma	0.18*	(0.03)	0.18*	(0.03)
Bachelor's Degree	-0.10*	(0.04)	-0.10*	(0.04)
Urbanization	-1.40*	(0.45)	-1.37*	(0.45)
Black, logged	-0.54*	(0.16)	-0.57*	(0.16)
Other Non-White, logged	-0.87*	(0.23)	-0.85*	(0.22)
Latino, logged	0.03	(0.27)	0.02	(0.27)
Foreign, logged	0.33†	(0.19)	0.34†	(0.19)
Rep 2016 Vote	-0.15*	(0.01)	-0.15*	(0.01)
Constant	3.32*	(0.82)	3.41*	(0.82)
Spatial Dependence in Vote, ρ	0.46*	(0.02)	0.46*	(0.02)
σ	4.77		4.78	
Obs.	2414		2414	

Notes: $^*p<.05$, $^\dagger p<0.1$ (two-tailed). State-level fixed effects are not shown.

Table 9: Change in Republican Vote Share Between 2016 and 2018 Elections as a Function of Soy Production, Accounting for Spatial Dependence in the Error Term

	All counties			
Soy Production	-0.70†	(0.37)		
Soy Sales			-1.55‡	(1.17)
GDP/cap., logged	0.19	(0.26)	0.18	(0.26)
(GDP/cap., logged)^2	0.10	(0.23)	-0.08	(0.23)
Unemployment	0.01	(0.02)	0.01	(0.02)
High-school Diploma	0.16*	(0.03)	0.16*	(0.03)
Bachelor's Degree	-0.12*	(0.04)	-0.12*	(0.04)
Urbanization	-1.15*	(0.47)	-1.11*	(0.46)
Black, logged	0.76*	(0.19)	-0.78*	(0.19)
Other Non-White, logged	-1.02*	(0.24)	-1.01*	(0.24)
Latino, logged	0.03	(0.29)	-0.05	(0.29)
Foreign, logged	0.26‡	(0.19)	0.26‡	(0.19)
Rep 2016 Vote	-0.18*	(0.01)	-0.18*	(0.01)
Constant	6.62*	(1.35)	6.71*	(1.35)
Spatial Dependence in the Error λ	0.56*	(0.02)	0.56*	(0.02)
σ	4.65		4.65	
Obs.	2414		2414	

Notes: $^{*}p$ <.05, $^{\dagger}p$ <0.1 (two-tailed); $^{\ddagger}p$ <0.1 (one-tailed). State-level fixed effects are not shown.

A Matched-Data Design

Soy counties may be unique in many ways that are not easy to capture within a regression framework. Although one may never fully rule out the confounding variable concern within an observationnal study, we attempted to tighten our causal claims by implementing a matched-samples design. We matched counties that rely on soy production (treatment group) with those that do not using the Coarsened Exact Matching (CEM) approach (Iacus, King and Porro, 2012).

Our treatment variable—*Soy Production*—is continuous, so the first step in implementing a matching approach was to select a reasonable threshold value that would split the data into the treatment (soy-dependent counties) and control (not soy-dependent counties) groups. According to the USDA (2019), the average soybean yield in the US was about 40 bushels/acre, while the size of an average farm in the US is about 442 acres (an average family farm is 231 acres), and the typical corn-to-soy crop ratio is 13 to 10, or approximately 43% soy. A county with a single soy-producing farm—hardly a soy-dependent county—would produce about $442 \times 0.43 \times 40 = 7,602$ bushels of soy per year. Based on these numbers, we chose to use the cut-off value of 10,000 bushels, since in actuality, even a county with low soy-reliance is likely to have more than one soy farm, e.g. several small family farms. This is a very conservative threshold, as less than 4% of soy-producing counties produce 10,000 bushels or fewer. Our results, moreover, are robust to using other thresholds.

Matching was performed using the `cem` package in `R`. The CEM approach involves exact matching (pairs of observations in the treatment and control groups have the exact same values on all covariates) after coarsening of the continuous or ordinal variables. Coarsening involves dichotomizing or multichotomizing variables into discrete categories. As suggested by Iacus, King and Porro (2012), we selected the cutpoints to multichotomize our variables based on our empirical knowledge of the data, whenever possible.[8]

[8] Specifically, we divided the variable *Rep 2016 Vote* into four classes: (0,25), [25,50), [50,75), [75,100). After some experimenting, we found that the best balance on the *Unemployment* variable is achieved by dividing it into intervals of about 1% wide. The *GDP/cap* variable was divided into ten intervals based on

This procedure reduced our data to 87 observations in the treatment group that were matched to 82 observations in the control group.[9] Table 10 presents the descriptive statistics in the post-matched sample. None of the mean differences are statistically significant (all the t-statistics are very small), suggesting a successful match with the two groups being very similar. The overall χ^2 test also fails to reject the null that there are no differences between the treatment and control groups (the observed χ^2 is far below the critical value). While checking differences in means between the treatment and control groups is the first step in assessing the balance of the matched sample, the goal of matching is to not only balance the means, but to balance the entire empirical distributions in our sample (Iacus, King and Porro, 2012; King and Nielsen, 2019). Figure 4 overlays the density distributions of the treatment and control groups in the post-matched sample. As expected, the two sets of distributions are very close.

Finally, we re-estimated the main model of our analysis (Model 1 of Table 1) on the post-matched sample (Table 11).[10] Consistently with our previous models, *Soy Production*'s coefficient is negative and statistically significant. Among the controls, *High-School Diploma* is positive and statistically significant, while *Urbanization*, and *Rep 2016 Vote* are negative. These findings are also consistent with other models. Other variables are not significant; that some previously predictive variables cease to be so is not surprising in matched samples.

every tenth quantile. For coarsening *High School Diploma*, we chose the cutpoints of 10, 30, 40, and 50%. The variable *Bachelor's Degree* was coarsened using cutpoints of 10, 15, and 30%. The variable *Foreign* was categorized into "less than 1%," "1% to 5%," and "more than 5%." *Urbanization* was grouped into "0%" and ">0%." *Other Non-White* was categorized into "<10%" and "10% or more." Finally, when we did not have a good sense of how to categorize a variable with relation to its consequences for soybean production, as was the case with *Black*, *Latino*, we relied on the `cem`'s default option of using the Sturges method that algorithmically multichotomizes variables based on their range.

[9] To maximize the power of our analysis, we allowed for multiple matches between the two groups.

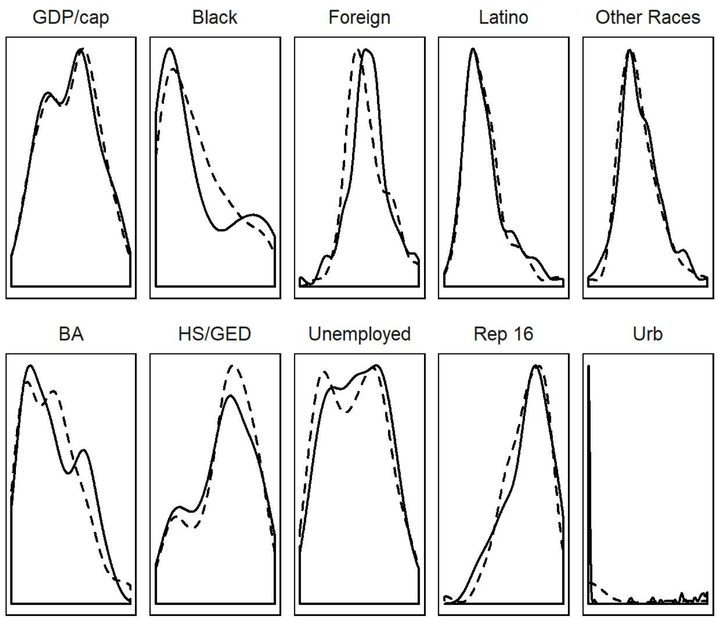
[10] Since CEM matches observations based on ranges in variables rather than exact values, it is advisable to include all of the variables used in matching as controls in the model run on the matched sample (Iacus, King and Porro, 2012).

Table 10: Balance in the Post-Matched Sample, Measured as the Difference in Means Between the Treated and Control Groups

Variable	Difference in Means	t-statistic
GDP/cap. (logged)	0.005	0.008
Unemployment	-0.786	-0.112
High-School Diploma	0.258	0.040
Bachelor's Degree	-0.304	-0.054
Urbanization	-0.021	-0.063
Black (logged)	0.066	0.059
Other Non-White (logged)	-0.030	-0.054
Latino (logged)	-0.014	-0.021
Foreign (logged)	-0.067	-0.066
Rep 2016 Vote	-0.957	-0.065
χ^2_{obs} (df=10)	4.770	
χ^2_{crit} (df=10)	18.307	
$\text{Obs}_{treatment}$	87	
$\text{Obs}_{control}$	82	

Notes: Difference in Means is calculated by subtracting the mean of the control group from the mean of the treatment group. The t-statistics are calculated by dividing the difference in means by the pooled standard deviation.

Figure 4: Balance in the Post-Matched Sample, Measured as the Overlap in the Empirical Density Distributions of the Treatment and Control Groups



Notes: Solid lines represent the control group and dashed lines represent the treatment group.

Table 11: Change in Republican Vote Share Between 2016 and 2018 Elections as a Function of Soy Production, Estimated on a Matched Sample

Soy Production	-2.33*	0.92
GDP/cap., logged	-1.17	(1.34)
(GDP/cap., logged)^2	-0.57	(1.23)
Unemployment	-0.05	(0.12)
High-school Diploma	0.45*	(0.15)
Bachelor's Degree	0.13	(0.20)
Urbanization	-5.18*	(2.45)
Black, logged	-0.13	(0.61)
Other Non-White, logged	0.62	(1.12)
Latino, logged	1.10	(1.32)
Foreign, logged	0.19	(0.89)
Rep 2016 Vote	-0.26*	(0.04)
Constant	-2.55*	(0.80)
Variance:		
States	10.86	
County	19.72	
Observations:		
County	169	
States	37	

Notes: $^*p<.05$, $^\dagger p<0.1$ (two-tailed). State-level random effects are not shown.

Difference-in-Difference Design

An alternative approach to validating causality claims with observational data is the difference-in-difference design (Angrist and Pischke, 2008). The idea is to approximate a repeated-design study, i.e. to take repeated measures from the same units. Since the units in the study stay the same, we can then attribute differences on the endogenous variable, Y, to the effect of the exogenous variable, X, while controlling for other factors. For our application, we implement the difference-in-difference design by taking advantage of the USDA's repeated measures of soybean production. Specifically, USDA has recently released the 2017 census numbers for county-level soy production and sales (date of release was April 11, 2019). The correlation between the 2012 data used to measure the primary independent variables is 0.97 for the *Soy Production* variable, and 0.98 for the *Soy Sales* variable.[11]

Next, we take a logged difference between *Soy Production 2017* and *Soy Production 2012*[12], and re-estimate models 1 and 3 using this variable on the subset of just soy-producing counties.[13] The results are presented in Table 12.

Our main results still hold, although in Model 1 *Difference in Soy Production* is only statistically significant at the 0.1 level in a one-tailed test.

[11] Although there is no evidence that soy farmers had any expectation of the tariffs from China—if they had, they presumably would have planted much less soy and more maize or other crop—using data from 2012 in our main analysis helps rule out any endogeneity that we may not have thought of.

[12] The values are rescaled to avoid taking a log of nonpositive numbers.

[13] Variable *Soy Sales* does not really allow for an analogous difference-in-difference test. For soy production, the expectation is that counties that increase production between 2012 and 2017 would be the most likely to decrease their support for the Republican party in the aftermath of China tariffs, as these counties experience the biggest losses in sales. For the soy-sales variable, the logic is not this straightforward: increase in sales is not necessarily correlated with that in production. In fact, when the tariffs hit, areas with high production likely experienced the largest decrease in sales.

Table 12: Change in Republican Vote Share Between 2016 and 2018 Elections as a Function of Soy Production, Estimated Using the Difference in Soy Production

	All counties		*Single-District Counties*	
Difference in Soy Production	-0.60‡	(0.38)	-0.81*	(0.31)
GDP/cap., logged	0.59†	(0.36)	0.33	(0.34)
(GDP/cap., logged)^2	0.10	(0.41)	0.13	(0.38)
Unemployment	0.04	(0.03)	0.07*	(0.03)
High-school Diploma	0.13*	(0.05)	0.10*	(0.04)
Bachelor's Degree	-0.14*	(0.06)	-0.14*	(0.06)
Urbanization	-2.41*	(0.65)	-2.29*	(0.63)
Black, logged	-0.86*	(0.21)	-0.25	(0.20)
Other Non-White, logged	-1.27*	(0.32)	-0.73*	(0.29)
Latino, logged	0.34	(0.38)	0.32	(0.35)
Foreign, logged	0.21	(0.26)	0.27	(0.23)
Rep 2016 Vote	-0.20*	(0.01)	-0.07*	(0.01)
ΔIncumbent			1.39*	(0.29)
Dist. Ideology			-0.14*	(0.03)
Constant	-3.48*	(0.53)	-3.71*	(0.65)
Variance:				
States	7.7		10.83	
County	25.6		16.80	
Observations:				
County	1578		1236	
States	40		30	

Notes: $^{*}p$ <.05, $^{\dagger}p$ <0.1 (two-tailed), $^{\ddagger}p$ <0.1 (one-tailed). State-level random effects are not shown.

A Replication Using 2017 Soy Data

Finally, we re-estimate our analysis using the recently released 2017 data on soy production, since in the main analysis we used older, 2012 data, in an attempt to rule out any endogeneity between expected tariffs and the amount of soy production. Our results are invariant to this choice.

Table 13: Change in Republican Vote Share Between 2016 and 2018 Elections as a Function of Soy Production, Using 2017 Data on Soy Production

	All counties				*Single-District Counties*			
Soy Production, 2017	-0.96*	(0.25)			-1.01*	(0.24)		
Soy Sales, 2017			-3.45*	(0.98)			-3.46*	(0.93)
GDP/cap., logged	0.62*	(0.30)	0.62*	(0.30)	0.24	(0.32)	0.23	(0.32)
(GDP/cap., logged)^2	-0.24	(0.27)	-0.21	(0.27)	0.14	(0.34)	0.19	(0.34)
Unemployment	-0.01	(0.02)	0.01	(0.02)	-0.01	(0.03)	0.01	(0.03)
High-school Diploma	0.17*	(0.04)	0.17*	(0.04)	0.19*	(0.04)	0.19*	(0.04)
Bachelor's Degree	-0.15*	(0.04)	-0.15*	(0.04)	-0.06	(0.05)	-0.06	(0.05)
Urbanization	-2.23*	(0.50)	-2.17*	(0.50)	-2.60*	(0.61)	-2.55*	(0.61)
Black, logged	-0.63*	(0.17)	-0.67*	(0.17)	-0.24	(0.18)	-0.28	(0.18)
Other Non-White, logged	-0.97*	(0.25)	-0.95*	(0.25)	-0.58*	(0.26)	-0.56*	(0.26)
Latino, logged	0.04	(0.29)	0.03	(0.29)	0.39	(0.33)	0.37	(0.33)
Foreign, logged	0.34	(0.21)	0.35	(0.21)	0.35	(0.21)	0.34	(0.21)
Rep 2016 Vote	-0.18*	(0.01)	-0.18*	(0.01)	-0.09*	(0.01)	-0.09*	(0.01)
ΔIncumbent					1.65*	(0.29)	1.66*	(0.29)
Dist. Ideology					-0.12*	(0.02)	-0.12*	(0.02)
Constant	-3.56*	(0.46)	-3.55*	(0.46)	-4.11*	(0.61)	-4.10*	(0.61)
Variance:								
States	8.68		8.79		10.30		10.28	
County	28.76		28.80		20.73		20.78	
Observations:								
County	2414		2414		1534		1534	
States	49		49		31		31	

Notes: $^*p$ <.05, $^\dagger p$ <0.1 (two-tailed). State-level random effects are not shown.