Online Appendix for
Policy Impact and Voter Mobilization: Evidence from Farmers' Trade War Experiences

Contents

A Detailed Data Description

A.1 FSA Payment Records

Through a series of Freedom of Information Act (FOIA) requests, we obtained payment data from the USDA Farm Service Agency (FSA) in two distinct formats. First, we obtained a series of annual files that together document nearly the universe of USDA farm program payments for 2004–2020 at the transaction level. Over the past few decades, USDA farm programs have generally fallen into one of three bins: (1) *commodity programs*, in which farmers are given financial support to grow crops, (2) *disaster programs*, which provide financial relief to farmers and ranchers harmed by hurricanes, droughts, frost, wildfires, tornadoes, and other natural disasters, and (3) *conservation programs*, which pay farmers to leave farmland fallow for the span of a 10–15 year lease. The yearly payment files we obtained feature the universe of Market Facilitation Program (MFP) payments, in addition to payments issued through the three traditional categories of farm support. Each transaction record lists the name of the recipient, the recipient's mailing address, the payment amount, the name of the program, the payment disbursement date, and the FSA county office issuing the payment. For clarity, we adopt the FSA's terminology and refer to these datasets as "name-address-payment" files.

Through a second group of FOIA requests, we obtained a patchwork of transaction-level databases covering 2004-2018 in older formats that feature internal recipient identifiers and (for certain key programs) attributions of payments to particular crops. Among the databases obtained was a set of records for MFP payments issued in calendar year 2018. This separate tabulation of MFP records contains all of the identifying fields in the name-address-payment files, but is organized at the transaction-crop level, and thus allows us to distinguish how much of each payment is attributed to, say, corn or soybean production. By contrast, MFP payments in the name-address-payment files have been aggregated to the MFP subprogram level, such that we can only distinguish payments for "commodity crops" (corn, cotton, sorghum, soybeans, wheat), "animal products" (milk or hogs), or "specialty crops" (almonds, cherries). Additionally, the separate calendar year 2018 MFP tabulation features the USDA's distinct customer identifiers (which were discontinued after 2018, and thus not provided with the name-address-payment files), as well as the "record creation date" for each MFP transaction. The latter date is generally one business day prior to the first disbursement date listed in the name-address-payment files, and thus constitutes the best available indicator of when program enrollment actually occurred.

Given the importance of crop-specific MFP payments to our research design, our main analyses focus exclusively on individual agricultural producers featured in the separate 2018 MFP tabulation. We nonetheless use the set of name-address-payment files to filter out farms that received some of their 2018 (program-year) payments in (calendar-year) 2019. Using the "name-address-payment database" of 2018 MFP payments—which also contains payments released after CY 2018 but lacks information on which commodities are enrolled—we limit our sample to farms in which all payments are reflected in our commodity-level tabulation. Using measures of recipients' historical production inferred from past commodity-level program payment records, we further limit our sample to farms that enrolled each crop in the MFP that historically constituted a major fraction of harvested production. These two methods together screen for farms for which our MFP records are very likely to reflect the full extent of 2018 production, and thereby allow us to minimize measurement error in the three policy outcome "treatments" we construct. See Online Appendices A.4 and A.5 for further details. Finally, we drop all farms for which recipients' MFP payment limits are binding, and limit to farms with at least 10 acres of cropland that reported producing one or more of the five major MFP-eligible crops in their MFP application, but none of the other four covered commodities (milk, hogs, almonds, cherries).[1]

A.2 L2 Voter and Commercial Files

Individual-level turnout in the 2018 general election and many of our controls come from national voter and consumer files provided by the vendor L2. L2 maintains panel data on individual voter turnout for over 180 million voters. Their national voter file provides unique identifiers for each voter, tracks individual voters who change addresses across election cycles, and is augmented by a number of demographic fields either provided in the constituent state

[1]We make this last restriction for a few reasons. First, we include a control for historical farm size in our main analyses, but we are only able to construct this measure for field crops. Second, the payment basis for animal products is not a perfect measure of 2018 production; see Online Appendix A.4 for details. Finally, we do not know of estimates of tariff-induced price declines for cherries and almonds.

voter files or merged in from other commercial sources. L2 features turnout histories for each state (and D.C.) in each election cycle from 2004 onward, and for some areas it features records as far back as the late 1980s. L2's voter files contain numerous, useful covariates that we augment by merging in L2's separate collection of state commercial files, which feature detailed data on over 200 million U.S. consumers.

We take great care to consider the particular panel nature of voter file turnout history data. State voter rolls evolve over time, adding voters as they register to vote and removing others as they become inactive or move out of state. As such, the "voter files" that researchers work with to study individual-level turnout decisions are actually snapshots of states' administrative databases at given points in time. This feature of voter files raises concerns for causal inference, as the periodic removal of inactive voters may cause survivorship bias if the voter file snapshot reflects the membership of a state's voter rolls *after* a treatment or event of interest has transpired. To mitigate such biases, we use L2 national releases from February 2018, June 2019, and May 2021, and limit our analysis to individuals featured in the February 2018 release. We obtain one of our two central outcomes in this paper—turnout in the 2018 general election—by creating a variable that takes a value of 1 if such a voter is noted to have turned out in 2018 in either the 2019 or 2021 releases, and a value of 0 otherwise.

Importantly for our study, L2 has a party affiliation field that reflects each registered voter's declared party preference in the 35 states (plus the District of Columbia) that collect such information. In the remaining 15 states,[2] L2 party affiliation reflects a modeled "likely" party affiliation based on supervised learning algorithms that take into account an array of public and propriety data, from primary election participation to local election results and voter file demographics.[3] After matching transactions from the FSA payments data to individuals in the consolidated L2 voter and consumer files (see Dataverse Materials Section E), we flag

[2]The 15 states with modeled party affiliation are HI, IL, WA, MT, ND, MN, WI, MI, VT, SC, MO, AL, TX, VA, and GA.

[3]See Spenkuch, Teso, and Xu (2021) for a discussion of L2's party affiliation field.

individual agricultural producers as “Republican” if they receive this label in the voter file, and categorize all other registered voters as “non-Republicans.”

A.3 Campaign Contribution Records

Farm-level measures of campaign contributions rely on itemized contribution records in the Database on Ideology, Money in Politics, and Elections (DIME) (Bonica, 2014). Adam Bonica generously provided us with a pre-release version of the DIME 4.0 database that extends coverage through the 2020 election cycle. This extended database features over 600 million itemized donations made between 1979 and 2020. Critically, DIME assigns unique identifiers to individual donors that track their donations across recipients and election cycles. As discussed in detail in Dataverse Materials E, we link each farm in our USDA database of farm program records to a distinct set of DIME contributor identifiers. Having done so, each transaction in DIME is associated with at most one distinct farm ID.

We utilize several pieces of information contained in the DIME transaction records. Several fields are used for record linkage, including contributor name, address, occupation, and employer. The other fields we use include the transaction amount, each recipient’s name and party affiliation, and Bonica’s measure of each recipient’s ideological ideal point: the common-space campaign finance score (“CFscore”).

Using a combination of the party affiliation fields and manual review, we calculate the dollar amount and transaction count of each farm’s itemized contributions to (a) Republican recipients, (b) Democratic recipients, (c) President Trump’s campaign and affiliated PACs, and (d) other recipients. We include PACS closely affiliated with the Republican Party and Democratic Party in our Republican and Democratic contribution figures, respectively. We aggregate all contribution measures to the farm level, because farm units within our data build generally correspond to distinct households, and political contributions are plausibly a household financial decision.

CFscores provide an appealing way to capture contributing farms' ideological lean in a single parsimonious measure. The CFscore places political contributors and recipients across all levels of US politics and across time on a unidimensional spectrum of left-right political ideology. This measure is scaled such that it is centered at zero and has standard deviation one. Importantly, the CFscore is a static measure: a single value is assigned to a contributor or recipient profile for their entire 1979-2020 contribution history. The fact that this measure is partly based off of 2018-2020 contributions suggests that we cannot be sure that contributors' CFscores embody a pre-treatment measure of individuals' political ideology. Consequently, we construct a farm-level pre-treatment CFscore by identifying all contributions made by a farm *prior* to 2018 for which the recipient has been assigned a CFscore. We then take an average of these pre-2018 recipients' CFscores weighted by contribution amount to arrive at a farm's pre-2018 CFscore. Among the 122,157 farms in our main analysis dataset, we are able to assign a pre-2018 CFscore to 27,060 (22%). We impute a default score of zero for the remaining farms.

For our analysis of farm-level contributions, we allow effects to be heterogeneous by partisan affiliation (as we do in our turnout analyses). However, we partition the sample according to contribution history, because (a) farms do not have a party registration, and (b) farms that do not have a history of contributing are fundamentally distinct from those who do. We thus break up our sample into "farms with a distinctly Republican contribution history," "farms with a distinctly Democratic contribution history," and "all other farms." We consider a farm to have a "distinctly Republican" contribution history if it satisfies three conditions: (i) it is associated with some contribution to a Republican candidate or PAC prior to 2018, (ii) it is associated with a greater dollar amount of pre-2018 contributions to Republicans than Democrats, and (iii) if it is assigned a pre-2018 CFscore, this CFscore is strictly greater than zero (indicating a history of supporting conservative candidates). The criteria for a "distinctly Democratic" contribution history mirror this exactly, and all farms who do not fall into one of these two bins are included in the "all other farms" category.

A.4 Construction of Policy Outcome Measures

We study the effects of changes in individual producers' short-run economic outcomes resulting from the 2018 trade war and the Market Faciliation Program. We consider three measures of policy outcomes in this vein: (1) 2018 MFP benefits net of 2018/2019 marketing year revenue lost due to commodity-specific price declines caused by retaliatory tariffs, (2) MFP compensation as a share of tariff-induced losses, and (3) whether or not an individual was "made whole" by the MFP, which corresponds to whether the first measure exceeds \$0 and equivalently whether the second exceeds 100%. Each of these measures requires a measure of an individual's MFP benefits and tariff-induced losses. In our survey analysis, we estimate both of these quantities from each respondent's reported 2018 corn and soy acreage in conjunction with their primary county of operation. In our turnout and contribution analyses, we observe MFP payments and use them to estimate tariff-induced losses. The resulting farm-level estimates are plausible because the MFP was paid out using a simple, known formula, and because a relatively large number of studies have estimated the impact of the 2018 trade war on agricultural commodity prices.

The 2018 MFP paid out \$0.01 per certified harvested bushel of corn, \$0.06 per pound of cotton, \$0.86 per bushel of sorghum, \$1.65 per bushel of soybeans, and \$0.14 per bushel of wheat. As such, we estimate harvest quantities for each farm in our survey sample by multiplying each farm's 2018 average county crop yields by planted acreage; we then obtain crop-specific MFP payments by multiplying harvest estimates by their respective MFP rates. We move in the opposite direction in building treatment measures for our turnout analysis; since we observe commodity-specific payments, we divide farmers' recorded payments by their respective rate to obtain the amount of each of these crops that the farmer harvested in 2018.[4]

[4] The 2018 MFP limited payments to \$125,000 per recipient each separately for dairy, hogs, and field crops.

The 2018 MFP also paid agricultural producers $8.00 per head for each live hog on August 1, 2018, and $0.12 per hundredweight of milk produced during a historical benchmark period.[5] Thus, we can also infer the size of recipients' hog and dairy operations at the trade war's commencement. However, the resulting figures are somewhat less useful for us than those obtained for commodity crops. Hogs and milk are not quite as homogeneous commodities as any of the five field crops; hogs are generally priced by weight (not per head) and milk is sold at different prices depending on which of four tiers it falls into under the Federal Milk Order System. Moreover, we are only able to infer dairies' recent historical production. As such, our main analyses focus only on the five major field crops (for which we can obtain a damage measure with minimal measurement error), and we limit our analysis of hog farmers and dairy owners to robustness checks.

With measures of production in hand for our survey and turnout analyses, we obtain farm-level measures of expected revenue for each commodity by multiplying production (in bushels or pounds) by expected commodity prices. Following Janzen and Hendricks (2020), we use USDA price forecasts published on May 10, 2018 as a benchmark to gauge MFP receipts and tariff-induced price declines against farmers' pre-trade war revenue expectations.[6] Specifically, the USDA forecast that farmers would receive $3.80 per bushel of corn, $0.65 per pound of

We drop producers from our sample if they meet (or exceed) any of these caps, as for these individuals we cannot infer 2018 production from MFP payments alone. This drops 2.6% of our sample. Note that some individuals were associated with multiple legal entities in the FSA payment system, and thus remain in our sample despite receiving total benefits in excess of $125,000.

[5]The MFP 2018 dairy rate was paid on the highest annual milk production marketed during the full calendar years of 2011, 2012, and 2013. However, only dairies in operation on June 1, 2018 were eligible for this payment.

[6]We use the midpoints of the USDA's commodity-specific forecasted price ranges published in the May 10, 2018 World Agricultural Supply and Demand Estimates (WASDE) report, available at https://usda.library.cornell.edu/concern/publications/3t945q76s?locale=en. This is the earliest WASDE report forecasting prices for the 2018/2019 crop marketing year, and its analysis makes no mention of the coming trade war. Indeed, it seems unlikely that either market or government entities anticipated trade war impacts at this point, as U.S. and Brazilian soybean export prices did not begin to diverge until mid-June, when China announced its 25% tariff on U.S. soybeans (see Figure 4 in Regmi (2019)).

cotton, \$3.60 per bushel of sorghum, \$10.00 per bushel of soybeans, and \$5.00 per bushel of wheat. In our robustness checks that take into account covered animal products, we use the USDA's February 2018 forecast of the average milk price in the fourth quarter of 2018[7] (\$16.60 per hundredweight), and the (ex-ante) expected 2018 price per hog (\$124.44) calculated by Swanson et al. (2019).

To gauge the share of revenue lost from tariff-induced price declines in 2018, we turn to published estimates from the agricultural economics literature. Starting with the most updated versions of papers reviewed by Janzen and Hendricks (2020), we ultimately find 10 studies that estimate the effect of retaliatory tariffs on prices received by U.S. agricultural producers. The most cited of these studies, Adjemian, Smith, and He (2021), uses the relative price of a substitute method to conclude that China's 25% retaliatory tariffs on U.S. soybean imports depressed U.S. soybean export prices between late-June and late-November 2018. The authors' methodology treats Brazilian producers—the second largest source of Chinese soybean imports before 2018—as a comparison group, and identifies the effects of retaliatory tariffs through structural breaks in the ratio of U.S. and Brazillian export prices. They estimate that prices received by U.S. producers were \$0.74 lower on average across the five-month period; this amounts to 7.4% of the USDA's forecasted 2018/2019 marketing year price, and 45% of the rate at which the 2018 MFP compensated soybean farmers. In a different time series approach, Swanson et al. (2019) construct a counterfactual price trend for corn, soybeans, and hogs by estimating the historical relationship between harvest-time price declines (relative to pre-harvest crop insurance prices) and realized levels of production. The authors estimate that counterfactual prices in October 2018 exceeded actual prices by \$1.02 per bushel of soybeans, \$0.08 per bushel of corn, and \$2.21 per hog, amounting to 10.2%, 2.1%, and 1.8% of expected prices and 62%, 800%, and 28% of 2018 MFP rates, respectively.

[7] See the February 16, 2021 USDA Livestock, Dairy, and Poultry Outlook report, https://www.ers.usda.gov/publications/pub-details/?pubid=100519.

Each of the remaining eight studies estimates the effect of retaliatory tariffs by calibrating trade models with pre-trade war agricultural market parameters, and then simulating the relevant policy changes. While each study specifies a full model of supply and demand within the relevant market(s), each ultimately features a distinct modeling approach. Zheng et al. (2018) use a version of the Global Simulation Model (GSIM), an Armington partial equilibrium model of trade that was also the basis for the USDA's calculations underpinning the 2018 MFP payment rates. Balistreri et al. (2018), Taheripour and Tyner (2018), and Yuan et al. (2020) each rely on particular versions of the Global Trade Analysis Project (GTAP) computable general equilibrium model. On the other hand, Sabala and Devadoss (2019) develop and calibrate a novel spatial equilibrium trade model, and the remaining three studies apply the particular agricultural trade modeling systems developed by research centers at Iowa State University (CARD Model, Elobeid et al. (2021)), University of Missouri (FAPRI-MU, Westhoff, Davids, and Soon (2019)), and Texas Tech University (World Fiber Model, Liu and Hudson (2019)).

Table OA1: Estimated Producer Price Declines Caused by 2018 Tariffs

	Soybeans	Corn	Wheat	Sorghum	Cotton	Hogs	Dairy
Time Series Analyses							
Adjemian et al (2021)	7.4%	—	—	—	—	—	—
Swanson et al (2019)	10.2%	2.1%	—	—	—	1.8%	—
Trade Model Estimates							
Balistreri et al (2018)	10.0%	4.0%	—	—	—	—	—
Elobeid et al (2021)	14.8%	3.6%	3.9%	—	—	2.1%	—
Liu and Hudson (2019)	—	—	—	—	1.5%	—	—
Sabala and Devadoss (2019)	11.9%	—	—	—	—	—	—
Taheripour and Tyner (2018)	4.9%	1.5%	1.1%	2.1%	—	—	0.5%
Westhoff et al (2019)	9.4%	3.1%	2.6%	10.0%	2.6%	1.6%	0.2%
Yuan et al (2020)	—	—	—	—	0.9%	—	—
Zheng et al (2018)	3.9%	—	—	10.6%	1.2%	0.6%	—

Notes: When a study features an estimate in terms of dollars and a % of a specified baseline, we take the dollar amount and divide it by the USDA's May 2018 forecasted 2018/2019 marketing year price.

Price impact estimates from each of these ten studies are presented in Table OA1. Altogether, eight studies estimate price impacts for soybeans, five for corn, three for wheat, three for sorghum, four for cotton, four for hogs, and two for dairy. In line with the conclusion of Janzen and Hendricks (2020), these studies unanimously find that MFP payment rates for soybeans, sorghum, and cotton exceeded short-run price impacts of the 2018 trade war, but undercompensated corn farmers. However, given the diversity of methodological approaches, there is (perhaps unsurprisingly) some dispersion among the estimates for particular commodities. Rather than litigate the relative advantages and disadvantages of different studies' methodologies, we obtain price impact measures for our main analyses by assuming that the true impact of the trade war is likely somewhere near the average of the different approaches. For our preferred measure of trade war damage (which we use for our main results), we consider only the five major field crops, and take the simple average of estimated price impacts across the ten studies featured in Table OA1. Then, as a robustness check, we replicate our main analyses using four alternative aggregations of these commodity-specific estimates. In increasing order of restrictiveness, we consider: (a) the simple average across all studies for all commodities (five field crops, hogs, dairy), (b) the simple average across all studies for the five field crops and hogs, (c) averaging estimates with equal weight given to the two high-level methodological approaches (time series analysis / trade model simulation) for each of the five field crops, and (d) taking the average estimates for corn and soybeans among only the time series analyses. The resulting commodity-by-commodity aggregates are presented in Table OA2. Note that we only calculate trade war damage under each aggregation method for producers of commodities included in said aggregation; as such, none of the producers in our main specifications reported raising hogs or running a dairy in 2018. To compute tariff-induced losses for our survey, turnout, and contribution analyses, we take the aforementioned revenue measures and multiply them by the proportional declines features in Table OA2.

Table OA2: Methods for Aggregating Price Impact Estimates

Commodities	Aggregation	N	Soybeans	Corn	Wheat	Sorghum	Cotton	Hogs	Dairy
Crops, Hogs, Dairy	Simple Avg	264,407	9.1%	2.9%	2.5%	7.6%	1.5%	1.5%	0.4%
Crops, Hogs	Simple Avg	246,891	9.1%	2.9%	2.5%	7.6%	1.5%	1.5%	—
Crops	**Simple Avg**	**242,575**	**9.1%**	**2.9%**	**2.5%**	**7.6%**	**1.5%**	—	—
Crops	Avg by Method	242,575	9.0%	2.6%	2.5%	7.6%	1.5%	—	—
Soybeans, Corn	Avg Time Series	170,357	8.8%	2.1%	—	—	—	—	—

Note: Third row depicts parameters reflected in the net benefit measure used in the main text.

A.5 Construction of Historical Farm Size Measure

To control for baseline differences in political engagement that may stem from long-standing differences in farm size (and therefore wealth), we construct a measure of historical farm acreage using each farm's prior payment records. We take advantage of the relatively simple connection between payments issued through flagship USDA farm programs in 2009-2012 and each recipient farm's historical acreage and yields. Since the passage of the 1996 farm bill, the USDA's predominant farm programs have made payments on historical planted acreage rather than current planting decisions. The 2002 farm bill maintained this program design principle in authorizing the Direct and Counter-Cyclical Program (DCP), which made payments on a farm's "base acres," which mostly reflected the farm's plantings of covered commodities between 1998 and 2001. Farms enrolled in the DCP received a "direct payment" each year, a constant annual sum paid out at commodity-specific rates according to base acreage and yields. Farms also received a conditional "counter-cyclical" payment when prices of particular commodities fell below statutorily-fixed thresholds. In the 2008 farm bill (in effect between 2009 and 2013), farms had the option to enroll in the Average Crop Revenue Election (ACRE) program instead of the DCP, which traded a 20% reduction in the direct payment rate for a counter-cyclical payment that would be made on current plantings instead of base acres.

By construction of our turnout sample, all farms we study enrolled in either DCP or ACRE between 2004 and 2012.[8] While DCP/ACRE made payments for 17 distinct crops, the five crops we consider in our turnout analysis accounted for over 92% of 2009-2012 enrolled base acreage. As such, inferring the basis of 2009-2012 DCP/ACRE payments for each farm in our sample should provide a compelling measure of longstanding farm size.[9]

Since we observe commodity-specific DCP/ACRE payment amounts for each farm in each year, we divide payment amounts by payment rates to infer each farm's "base production." Specifically, for each covered crop $c \in \mathcal{C}$, the DCP/ACRE formula specifies farm i's fixed annual direct payment in year $t \in \{2009, 2010, 2011, 2012\}$ as:

$$\text{Payment}_{itc} = \text{Base\_Acres}_{ic} \cdot \text{Acreage\_Prop}_t \cdot \text{Base\_Yield}_{ic} \cdot \text{Payment\_Rate}_c \cdot \text{ACRE\_adj}_i,$$

where Base_Acres_{ic} denotes the farm i's base acres associated with commodity c, Acreage_Prop_t reflects the fact that the 2008 farm bill specified payments to be made on 83.3% of base acres in 2009-2011 and 85% of base acres in 2012, Base_Yield_{ic} denotes the farm's historical yields for commodity c, Payment_Rate_c denotes the direct payment rate per harvested unit of commodity c (fixed for the duration of the farm bill), and ACRE_adj_i denotes the fact that farmers electing the ACRE option incurred a 20% reduction in direct payments. Since we observe each farm's county of operation,[10] we proxy each farm's base yield for each commodity with their county's historical yields, and then estimate farm i's total enrolled base acreage in year t as

$$\widehat{\text{Base\_Acres}}_{it} = \sum_{c \in \mathcal{C}} \frac{\text{Payment}_{itc}}{\text{Acreage\_Prop}_t \cdot \text{County\_Avg\_Yield}_{ic} \cdot \text{Payment\_Rate}_c \cdot \text{ACRE\_adj}_i}.$$

[8]While the DCP/ACRE programs were in effect between 2004 and 2013, our commodity-level transaction data for DCP/ACRE only spans 2004-2012.

[9]Indeed, we validate the resulting measure of farm size in Dataverse Materials B.

[10]We observe the FSA county office through which each transaction is processed. According to a FSA employee we spoke with, this is generally a very good indication of where the actual farm in question is located.

We average the resulting measure across 2009-2012 to obtain a pre-treatment measure of longstanding farm size.

As referenced in the main manuscript ("Data on Policy Outcomes, Voter Turnout, and Campaign Contributions"), limiting our sample to 2004-2012 DCP/ACRE recipients also comes with the advantage of allowing us to screen out farms whose records may not reflect the totality of their 2018 harvest. Enrollments in the 2018 MFP for a given commodity were made after the farm finished harvesting said commodity. Since enrollments were made using formally certified harvest records, MFP transactions within the $125,000 payment cap should precisely reflect the farm's total 2018 harvest for each enrolled commodity. Farmers we have spoken with have confirmed that it would be implausible for a farm to enroll anything other than their full harvested amount of a given crop. However, we consider the possibility that certain farmers may not have bothered to enroll *particular crops*—particularly corn, given the pittance it earned from the MFP. To mitigate this, we took each farm's DCP records and backed out "base production" of each crop $c \in \mathcal{C}$ (in bushels or pounds) as

$$\widehat{\text{Base\_Production}}_{itc} = \frac{\text{Payment}_{itc}}{\text{Acreage\_Prop}_t \cdot \text{Payment\_Rate}_c \cdot \text{ACRE\_adj}_i}.$$

We then multiplied these base production measures by average 2009-2012 commodity prices to obtain a measure of "base revenue" that is comparable across crops. We dropped any farm from our main turnout analysis sample if (a) any MFP-eligible crop constituted at least a third of base revenue and (b) said crop was not enrolled in the MFP.

A.6 Survey of Midwestern Corn and Soy Growers

Our analysis of farmer attitudes towards the MFP relies on survey data first reported in Li et al. (2023), and also analyzed in Li et al. (2022). In March 2019, the authors sent survey invitations to a random sample of 3,000 corn and soy farmers operating at least 250 acres in Iowa, Illinois, and Minnesota (three of the top four corn and soybean producing states). The firm Survey Sampling International recruited the sample based on government records of benefit receipt. The initial invitations referred potential respondents to an online survey; the authors followed up with farmers who did not complete the online survey by mailing printed questionnaires on April 15 and May 7.

The authors kindly agreed to share a replication dataset with us. This dataset features responses from 783 farmers, and includes a number of useful items for our analysis: (1) planted acreage of corn, soybeans, and all other crops in 2013-2017 (average), 2018, and 2019 (planned), (2) an item asking respondents how informed they considered themselves with regards to the trade disruption, (3) an item testing respondents on their knowledge of the Market Facilitation Program by asking them to identify the correct soybean payment rate from a lineup of five rates, (4) an item gauging how helpful the farmers perceived the 2018 MFP to be, and (5) the respondent's primary county of operation.

As referenced in "Farmer Perceptions of the 2018 MFP" in the main text, we use items (2) and (3) from this list to conclude that respondents were generally well-informed about the trade war and the MFP. Among the farmers who reported any corn/soybean acreage in 2018 and 2013-2017, 7% claimed to be "slightly informed" about the trade war, while 42% considered themselves "moderately informed," 40% "very informed," and 12% "extremely informed." None identified as "not informed." More concretely, when asked to identify the MFP payment rate for soybeans out of a lineup of five options, over 90% correctly identified it as $1.65/bushel. We use the remaining fields to demonstrate that the perceived helpfulness of the MFP was generally increasing in soybean plantings and decreasing in corn plantings, and that better overall policy outcomes from the trade war and the MFP were associated with greater perceived MFP helpfulness.

Open-ended comments from respondents also reflected a relatively clear understanding of tariff-induced price declines and the Trump administration's relief package. In particular, several comments suggest that corn farmers realized that the \$0.01/bushel MFP payment rate fell short. Mirroring the stark contrast presented in Figure 1, one farmer noted that retaliatory tariffs "also dragged down corn prices," with another noting that "[f]utures corn prices were very impacted by [the] tariff announcement and a 1 cent/bushel [payment rate] was an insult." Two other farmers specifically noted that the corn rate was inadequate, with one also identifying corn being "pulled down by the soybean price" as the source of the disconnect between damages and compensation.

Since we use this survey data to explore the relationship between farmers' policy outcomes (by way of their crop portfolios) and policy attitudes, we limit our analysis sample to respondents who (a) reported positive corn/soy acreage in 2013-2017 and 2018 and (b) reported their perceived helpfulness of the MFP. These deletions leave us with 621 responses.

B Description of Covariates and Controls

Table OA3 describes all controls included in our main voter-level turnout analyses, as presented in the main text ("The Effect of Improved Policy Outcomes on Voter Turnout") and Dataverse Materials Sections H.1 and H.2. These include fields representing individual turnout and farm contribution histories, individual demographics, historical farm size, and geographic characteristics relating to voters' residential addresses. In addition to the fields listed in Table OA3, our robustness checks examining heterogeneous treatment effects occasionally include an additional covariate. For example, our analysis of heterogeneity by payment timing makes use of an indicator for whether an individual's first MFP record in the FSA system was created before Election Day 2018 (Figure DM37) or the number of days since Election Day (Figures DM38, DM39, DM40, and DM41). In our DML analyses, we do not need to one-hot-encode categorical variables or check for collinear feature combinations, as CatBoost (the supervised learning algorithm we use to estimate the first-stage conditional expectations q and m) handles categorical variables natively, and does not require the feature matrix to be nonsingular. Our measure of historical farm size was inferred from farm program payment information obtained via FOIA request (see Online Appendix Subsection A.5), and county-level Presidential margins in 2000 and 2004 are from data provided by the MIT Election Lab. Contribution fields are sourced from DIME. All other fields are sourced from L2's voter and commercial files. In the interest of ensuring that all covariates are observed pre-treatment whenever possible, we source these measures from the February 2018 snapshot of L2's voter files whenever available; this is our data source for relevant covariates for the vast majority of sample members. In the rare occasion in which covariates are only available from later sources, we obtain these measures from L2's 2021 commercial file, or L2's June 2019 or May 2021 snapshots of their voter files.

Similarly, Table OA4 presents controls used in our main farm-level campaign contribution analyses, as presented in the main text ("The Effect of Improved Policy Outcomes on Campaign Contributions") and Dataverse Materials Section H.3. Our large-scale analysis comparing affected farmer turnout to non-farmer turnout in Figure 11 relies on all covariates in Table OA3 save historical farm size and fields constructed from campaign contribution records.[11] Our large-scale analyses comparing affected farmer contributions to non-farmer contributions likewise rely on a subset of the covariates described in Tables OA3 and OA4. See Dataverse Materials G for a full list.

Table OA3: Description of Controls in Voter-Level Turnout Analyses

Field(s)	Description
`turnout_[cycle]` for `cycle` in 2008, 2010, 2012, 2014, 2016	Indicator for whether the individual voted in the specified general election.
	Continued on next page

[11]Given our focus to the broader electorate, we also do not limit our congressional district controls to the 200 most common districts, as we do in our between-farm analysis of voter turnout.

Table OA3 – continued from previous page

Field(s)	Description
turnout_[cycle] for cycle in $1992, 1994, \ldots, 2004, 2006$	Categorical variable specifying turnout records for the given general election. This variable takes a value of 4 if a vote was recorded in the individual's L2 turnout history; 3 if the individual was not yet 18 on Election Day; 2 if L2 does not have records for that state-cycle combination; 1 if turnout in the election was less than 20% among all individuals in the L2 voter file currently residing in said state; 0 if there is no record of a vote cast in said election, and none of the previous factors apply.
primary_turnout_[cycle] for cycle in $1992, 1994, \ldots, 2014, 2016$	Indicator variable specifying turnout records for the given primary election. Takes a value of 1 if a vote was recorded in the individual's L2 turnout history; 0 otherwise.
democrat	Indicator for Democratic party affiliation (L2 voter file); only included for the non-Republican effect estimates
education_5pt_[level] for level in 1,2,3,4,5	Indicators for highest level of education obtained; levels are "HS diploma", "some college or vocational/technical degree", "bachelor's degree", "graduate degree", or "missing"; left-out category is "less than HS diploma". In the instance in which the L2 voter and consumer profiles disagree (and neither is missing), we take the greater of the two.
white_not_hispanic	Ethnicity from L2; in the instance in which the L2 voter and consumer profiles disagree, we use the value from the voter file.
race_ethnicity_missing	Ethnicity from L2; in the instance in which the L2 voter and consumer profiles disagree, we use the value from the voter file.
protestant	Indicator for whether L2 classifies voter as Protestant.
catholic	Indicator for whether L2 classifies voter as Catholic.
female	Indicator for voter's gender.
age	Integer reflecting voter's age on Election Day 2018.
log_pop_density	Natural logarithm of the estimated number of adults per square mile calculated for all adults living within the voter's census block.
military_or_veteran	Indicator taking a value of 1 if the L2 voter file labels the individual as "military,veteran", the L2 commercial file labels them a "veteran", or the commercial file indicates that there is a veteran in the household.
christian_family	Indicator taking a value of 1 if the L2 commercial file considers the individual to be in the "Christian families" demographic.
gun_owner_or_concealed_carry	Indicator taking a value of 1 if either the L2 voter or commercial file notes that the individual is a gun owner or holds a concealed carry permit.
log_historical_acreage_09_12	Natural logarithm of estimate of average 2009-2012 acreage enrolled in flagship USDA farm programs. Proxies for farm's longstanding row crop acreage. See Online Appendix A.5 for details on construction of this measure.
county_GOP_pres_margin_[cycle] for cycle in 2000, 2004, 2008, 2012, 2016	County-level Republican two-party vote share margin in the specified presidential election.
precinct_turnout_G[YY] for YY denoting 2010, 2012, 2014, or 2016	General election turnout within the voter's precinct in the specified general election.
precinct_turnout_G[YY]_[party] for YY denoting 2010, 2012, 2014, or 2016 and party denoting Republicans, Democrats, or independents	General election turnout among voters affiliated with the specified party within the voter's precinct in the specified general election.

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Table OA3 – continued from previous page

Field(s)	Description
CIDs_active_before_2018_count	Number of distinct contributor IDs in Bonica's DIME 4.0 database that made itemized contributions prior to 2018 and were linked to the same farm as the voter.
total_amount_pre_2018	Total dollar amount of 1979-2017 itemized contributions made by DIME contributor profiles linked to the farm.
pre_2018_cfscore	Pre-2018 analogue of Bonica's (2014) common-space campaign finance score ("CFscore") measure of donor ideology. For each farm linked to contributors in DIME that made itemized contributions prior to 2018, we take the average of pre-2018 contribution recipients' CFscores, weighted by the dollar amounts of the respective donations. For farms not linked to pre-2018 contributions, we impute a value of 0.
rep_contribution_history	Indicates farm had a distinctly Republican pre-2018 contribution history. Takes a value of 1 if three conditions satisfied: (i) farm is associated with some contribution to a Republican candidate or PAC prior to 2018, (ii) farm is associated with a greater dollar amount of pre-2018 contributions to Republicans than Democrats, and (iii) if farm is assigned a pre-2018 CFscore, this CFscore is strictly greater than zero.
dem_contribution_history	Indicates farm had a distinctly Democratic pre-2018 contribution history. Takes a value of 1 if three conditions satisfied: (i) farm is associated with some contribution to a Democratic candidate or PAC prior to 2018, (ii) farm is associated with a greater dollar amount of pre-2018 contributions to Democrats than Republicans, and (iii) if farm is assigned a pre-2018 CFscore, this CFscore is strictly less than zero.
net_rep_amount_before_2005	Total dollar amount of farm's 1979-2004 political contributions to Republican candidates and PACs, minus total dollar amount to Democratic candidates and PACs.
net_rep_amount_[quarter] for quarter in 2005-Q1, 2005-Q2, ..., 2017-Q3, 2017-Q4	Total dollar amount of farm's political contributions to Republican candidates and PACs in the specified quarter, minus total dollar amount to Democratic candidates and PACs.
net_rep_amount_[quarter] for quarter in 2005-Q1, 2005-Q2, ..., 2017-Q3, 2017-Q4	Total dollar amount of farm's political contributions to Republican candidates and PACs in the specified quarter, minus total dollar amount to Democratic candidates and PACs.
rep_amount_[quarter] for quarter in 2016-Q1, 2016-Q2, 2016-Q3, 2016-Q4, 2017-Q1, 2017-Q2, 2017-Q3, 2017-Q4	Total dollar amount of farm's political contributions to Republican Party candidates and PACs in the specified quarter.
dem_amount_[quarter] for quarter in 2016-Q1, 2016-Q2, 2016-Q3, 2016-Q4, 2017-Q1, 2017-Q2, 2017-Q3, 2017-Q4	Total dollar amount of farm's political contributions to Democratic Party candidates and PACs in the specified quarter.
other_amount_[quarter] for quarter in 2016-Q1, 2016-Q2, 2016-Q3, 2016-Q4, 2017-Q1, 2017-Q2, 2017-Q3, 2017-Q4	Total dollar amount of farm's political contributions in the specified quarter to candidates and PACs not affiliated with the Republican or Democratic parties.

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Table OA3 – continued from previous page

Field(s)	Description
`consolidated_cong_district_[i]` for `i` in 1, . . . , 200	Indicator for whether voter resides in congressional district `i`, where districts have been sorted from most to least common within our sample. In practice, this serves as adding in district fixed effects into our set of controls. We limit this array of district indicators to the top 200 districts within our sample, as 98% of our sample resides within these districts, and this restriction substantially improves the computational performance of our DML estimators.

Table OA4: Description of Controls in Farm-Level Contribution Analyses

Field(s)	Description
`pre_2018_cfscore`	Pre-2018 analogue of Bonica's (2014) common-space campaign finance score ("CFscore") measure of donor ideology. For each farm linked to contributors in DIME that made itemized contributions prior to 2018, we take the average of pre-2018 contribution recipients' CFscores, weighted by the dollar amounts of the respective donations. For farms not linked to pre-2018 contributions, we impute a value of 0.
`rep_contribution_history`	Indicates farm had a distinctly Republican pre-2018 contribution history. Takes a value of 1 if three conditions satisfied: (i) farm is associated with some contribution to a Republican candidate or PAC prior to 2018, (ii) farm is associated with a greater dollar amount of pre-2018 contributions to Republicans than Democrats, and (iii) if farm is assigned a pre-2018 CFscore, this CFscore is strictly greater than zero.
`dem_contribution_history`	Indicates farm had a distinctly Democratic pre-2018 contribution history. Takes a value of 1 if three conditions satisfied: (i) farm is associated with some contribution to a Democratic candidate or PAC prior to 2018, (ii) farm is associated with a greater dollar amount of pre-2018 contributions to Democrats than Republicans, and (iii) if farm is assigned a pre-2018 CFscore, this CFscore is strictly less than zero.
`CIDs_active_before_2018_count`	Number of distinct contributor IDs in Bonica's DIME 4.0 database that made itemized contributions prior to 2018 and were linked to the farm.
`total_amount_pre_2018`	Total dollar amount of 1979-2017 itemized contributions made by DIME contributor profiles linked to the farm.
`log_historical_acreage_09_12`	Natural logarithm of estimate of average 2009-2012 acreage enrolled in flagship USDA farm programs. Proxies for farm's longstanding row crop acreage. See Online Appendix A.5 for details on construction of this measure.
`log_pop_density`	Natural logarithm of the estimated number of adults per square mile calculated for all adults living within the voter's census block; we take the average population density for voters linked to the farm, and then apply the log transformation.
`consolidated_cong_district_[i]` for `i` in 1, . . . , 200	Indicator for whether farm resides in congressional district `i`, where districts have been sorted from most to least common within our sample. In practice, this serves as adding in district fixed effects into our set of controls. We limit this array of district indicators to the top 200 districts within our sample, as 98% of our sample resides within these districts, and this restriction substantially improves the computational performance of our DML estimators.

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Table OA4 – continued from previous page

Field(s)	Description
county_GOP_pres_margin_[cycle] for cycle in 2000, 2004, 2008, 2012, 2016	County-level Republican two-party vote share margin in the specified presidential election; we take the average among voters linked to the farm.
precinct_turnout_G[YY] for YY denoting 2010, 2012, 2014, or 2016	General election turnout within the voter's precinct in the specified general election; we take the average among voters linked to the farm.
precinct_turnout_G[YY]_[party] for YY denoting 2010, 2012, 2014, or 2016 and party denoting Republicans, Democrats, or independents	General election turnout among voters affiliated with the specified party within the voter's precinct in the specified general election; we take the average among voters linked to the farm.
net_rep_amount_before_2005	Total dollar amount of farm's 1979-2004 political contributions to Republican candidates and PACs, minus total dollar amount to Democratic candidates and PACs.
net_rep_amount_[quarter] for quarter in 2005-Q1, 2005-Q2, ..., 2017-Q3, 2017-Q4	Total dollar amount of farm's political contributions to Republican candidates and PACs in the specified quarter, minus total dollar amount to Democratic candidates and PACs.
net_rep_trx_count_before_2005	Number of itemized contributions made to Republican candidates and PACs 1979-2004, minus number made to Democratic candidates and PACs.
net_rep_trx_count_[quarter] for quarter in 2005-Q1, 2005-Q2, ..., 2017-Q3, 2017-Q4	Number of itemized contributions made to Republican candidates and PACs in the specified quarter, minus number made to Democratic candidates and PACs.
[party]_amount_before_2005 for each party in "Republican", "Democrat", "Other"	Total dollar amount of farm's 1979-2004 political contributions to party candidates and PACs.
[party]_amount_[quarter] for quarter in 2005-Q1, 2005-Q2, ..., 2017-Q3, 2017-Q4 and for each party in "Republican", "Democrat", "Other"	Total dollar amount of farm's political contributions to party candidates and PACs in the specified quarter.
trump_amount_[quarter] for quarter in 2014-Q3, 2014-Q4, ..., 2017-Q3, 2017-Q4	Total dollar amount of farm's political contributions made to Trump campaign and affiliated PACs in the specified quarter.
[party]_trx_count_before_2005 for each party in "Republican", "Democrat", "Other"	Number of itemized contributions made to party candidates and PACs 1979-2004.
[party]_trx_count_[quarter] for quarter in 2005-Q1, 2005-Q2, ..., 2017-Q3, 2017-Q4 and for each party in "Republican", "Democrat", "Other"	Number of itemized contributions made to party candidates and PACs in the specified quarter.
trump_trx_count_[quarter] for quarter in 2014-Q3, 2014-Q4, ..., 2017-Q3, 2017-Q4	Number of itemized contributions made to Trump campaign and affiliated PACs in the specified quarter.
republican_voter_count	Number of Republican Party voters linked to the farm, per the February 2018 L2 voter file snapshot.
democratic_voter_count	Number of Democratic Party voters linked to the farm, per the February 2018 L2 voter file snapshot.
turnout_[cycle]_count for cycle in 2008, 2010, 2012, 2014, 2016	Number of voters linked to farm who turned out to vote in specified general election.

Continued on next page

Table OA4 – continued from previous page

Field(s)	Description
`primary_turnout_[cycle]_count` for `cycle` in $2008, 2010, 2012, 2014, 2016$	Number of voters linked to farm who turned out to vote in a primary election in the specified cycle.
	Number of Democratic Party voters linked to the farm, per the February 2018 L2 voter file snapshot.
`military_or_veteran_count`	Number of linked voters that the L2 voter file labels as "military,veteran", the L2 commercial file labels them a "veteran", or the commercial file indicates that there is a veteran in the household.
`christian_family_count`	Number of linked voters that the L2 commercial file considers to be in the "Christian families" demographic.
`gun_owner_or_concealed_carry_count`	Number of linked voters for whom either the L2 voter or commercial file notes that the individual is a gun owner or holds a concealed carry permit.
`precinct_turnout_G[YY]` for `YY` denoting 2014 or 2016	General election turnout within the voter's precinct in the specified general election; we take the average among voters linked to the farm.
`precinct_turnout_G[YY]_[party]` for `YY` denoting 2014 or 2016 and `party` denoting Republicans, Democrats, or independents	General election turnout among voters affiliated with the specified party within the voter's precinct in the specified general election; we take the average among voters linked to the farm.
`county_GOP_pres_margin_[cycle]` for cycle in 2008, 2012, 2016	County-level Republican two-party vote share margin in the specified presidential election; we take the average among voters linked to the farm.
`county_GOP_pres_margin_[cycle]` for cycle in 2008, 2012, 2016	County-level Republican two-party vote share margin in the specified presidential election; we take the average among voters linked to the farm.
`voter_[i]_age` for $i \in \{1, 2, 3\}$	Integer reflecting age on Election Day 2018 of the farm's `i`th oldest linked voter; if fewer than i voters have been linked, value defaults to -1.
`voter_[i]_female` for $i \in \{1, 2, 3\}$	Indicator for whether farm's `i`th oldest linked voter is female; if fewer than i voters have been linked, value defaults to -1.
`voter_[i]_ethnicity` for $i \in \{1, 2, 3\}$	Categorical variable indicating ethnicity of farm's `i`th oldest linked voter; if fewer than i voters have been linked, value defaults to -1.
`voter_[i]_education` for $i \in \{1, 2, 3\}$	Categorical variable indicating highest level of education achieved by farm's `i`th oldest linked voter; if fewer than i voters have been linked, value defaults to -1.
`voter_[i]_republican` for $i \in \{1, 2, 3\}$	Indicator for whether farm's `i`th oldest linked voter is listed as Republican in February 2018 L2 voter file snapshot; if fewer than i voters have been linked, value defaults to -1.
`voter_[i]_democrat` for $i \in \{1, 2, 3\}$	Indicator for whether farm's `i`th oldest linked voter is listed as Democrat in February 2018 L2 voter file snapshot; if fewer than i voters have been linked, value defaults to -1.
`voter_[i]_turnout_ge_[cycle]` for $i \in \{1, 2, 3\}$ and `cycle` denoting 2014 or 2016	Indicator for whether farm's `i`th oldest linked voter turned out to vote in the general election in the specified cycle; if fewer than i voters have been linked, value defaults to -1.
`voter_[i]_turnout_pe_[cycle]` for $i \in \{1, 2, 3\}$ and `cycle` denoting 2014 or 2016	Indicator for whether farm's `i`th oldest linked voter turned out to vote in the primary election in the specified cycle; if fewer than i voters have been linked, value defaults to -1.

C Contents of Dataverse Materials

Additional information is available in our secondary appendix ("Dataverse Materials"), accessible at:

https://doi.org/10.7910/DVN/S7TOGV

This includes: (1) a discussion of what might constitute a "typical" farm experiencing the trade war and MFP (and the calculations that went into Figure 2); (2) a validation exercise for our measures of historical farm size and 2018 crop portfolios; (3) additional descriptive statistics; (4) a discussion of pre-treatment covariate balance across the distributions of our policy disposition treatments; (5) a detailed description of the entity resolution and record linkage algorithms used to cluster USDA farm program recipients into distinct farms and link these farms to the L2 voter files and DIME database of itemized political contributions; (6) further details on our empirical strategy, including the mechanics of Double Machine Learning estimation and a discussion of our use of CatBoost to estimate the first-stage relationships $q(X_i) = \mathbb{E}[Y_i \mid X_i]$ and $m(X_i) = \mathbb{E}[B_i \mid X_i]$; (7) supporting information for the large-scale analyses presented in Figures 11 and 12, including a detailed description of how we categorized farms as "directly affected by the trade war" using 2013-2017 administrative data; (8) additional results and robustness checks for our survey, turnout, and contribution data analyses; and (9) a series of three tables listing all Double Machine Learning PLR estimates presented in this paper.

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