Farmers' Reactions to the US-China Trade War: Perceptions Versus Behaviors

Running Head: Farmers' Reactions to the US-China Trade War

Minghao Li, Assistant Professor, Department of Economics, Applied Statistics & International Business, New Mexico State University, minghao@nmsu.edu

Xi He, Department of Agricultural and Applied Economics, Virginia Tech University, xih@vt.edu

Wendong Zhang*, Assistant Professor, Dyson School of Applied Economics and Management, Cornell University, wendongz@cornell.edu

Shuyang Qu, Assistant Professor, Department of Agricultural Education and Studies, Iowa State University, squ@iastate.edu

Lulu Rodriguez, Global Programs Lead, Seed Science Center, Iowa State University, lulurod@iastate.edu

James M. Gbeda, Ph.D. Student, Department of Economics, Iowa State University, jmgbeda@iastate.edu

*: Corresponding Author

Acknowledgments and Funding Information: This research was supported by the Center for Agricultural and Rural Development (CARD) and the College of Agriculture and Life Sciences (CALS) at Iowa State University. We also acknowledge base support from Iowa Agriculture and Home Economics Experiment Station Hatch Project IOW05511 and the USDA National Institute of Food and Agriculture (NIFA) Hatch Project IOW04099 and grant 2019-67023-29414. The authors also thank Chad Hart, Nate Cook, Guang Han, Jonathan Hassid, Kelvin Leibold, and Yang Xie for feedback on earlier drafts.

Data Availability Statement: The data, survey questionnaire, and replication codes that support the findings of this study are openly available in Mendeley Data at https://data.mendeley.com/datasets/rn4jc6vt2f/1, reference number 10.17632/rn4jc6vt2f.1.

Farmers' Reactions to the US-China Trade War: Perceptions Versus Behaviors

Abstract: This study examines how the political alignments of Midwestern farmers, proxied by their consumption of partisan media, affect their perceptions of and responses to the US-China trade war. Our results indicate that farmers who consume conservative media perceive a lower income loss resulting from the trade war and view the Market Facilitation Program (MFP) as more helpful. Conversely, farmers who consume liberal media have the opposite perception biases. We found no evidence of any association between partisan media consumption and planting and risk management decisions. Overall, partisan bias exists despite financial interest at stake but does not affect behaviors.

KEYWORDS: Trade policies, US-China trade war, Political bias, Media bias

JEL CODES: D83, F68, F51, Q13, Q17

I. Introduction

In 2018, the United States increased tariffs on major trade partners, especially China, which reversed its long-term policy of reducing trade barriers (Fajgelbaum et al., 2020). With waves of US tariff increases and retaliatory tariffs from China, the trade conflict escalated into a trade war that profoundly impacted the global economy (Li et al., 2020). US farmers, a group with outsized political influence relative to their number (Anderson, Rausser, & Swinnen, 2013), became a focal point in the trade war. On the one hand, China imposed several waves of retaliatory tariffs on US agricultural exports (Bown & Kolb, 2021), targeting the Republican voter base (Fetzer & Schwarz, 2021). On the other hand, the MFP tends to over-compensate farmers in general (Janzen & Hendricks, 2020, Grant et al., 2021, Balistreri et al. 2020), especially in Republican counties (Choi & Lim, 2022). Previous studies suggest that US voters are responsive to trade policies related to China (Autor et al., 2020; Che et al., 2022), including the 2018 trade war. For example, Choi and Lim (2022) find that MFP payments net tariff-induced income loss increase the Republican vote. Similarly, Janzen et al. (2021) find that MFP payments increase voter turnout for President Trump.

However, two important research questions remain. The first is how to explain the heterogeneous and polarizing reactions to trade policies. For example, Autor et al. (2020) find that exposure to trade competition increases support for representatives from the local majority party, regardless of which party it is. Janzen et al. (2021) find that MFP payments only increase voter turnout for President Trump and do not induce "vote switching." Choi and Lim (2022) find that the impact of net MFP payments is high in solidly Republican states and almost negligible in solidly Democratic states. Following a strand of literature on partisan biases (see reviews in Bullock & Lenz, 2019; Jerit & Zhao, 2020), this study provides evidence that farmers' political alignments filter their perceptions of the trade war's impacts. Such partisan bias can explain why people with different political alignments react differently to the economic realities of the trade war.

The second research question is whether partisan bias spreads from political behaviors to economic decisions. Given that farmers perceive trade war impacts differently, they may also make different economic decisions on planting and risk management. However, the behavior differences will not realize if farmers are "cheerleading" (Bullock & Lenz, 2019; Jerit & Zhao, 2020) for the political party they support when reporting their perceptions. To answer this research question, we analyze how partisan bias impacts planting decisions and risk management practices, including storage, pre-harvest marketing, and the usage of non-spot markets.

This study focuses on how Midwestern farmers' perception of trade-war impacts and their economic responses differ by political alignments. Because our data does not include a direct measure of political alignment, the consumption of media sources with conservative or biases is used as proxies. Consumers with inherent partisan bias self-select into the audience of media sources with conservative or liberal biases (Prior, 2013; Stromback et al., 2012); they may acquire additional partisan bias through exposure to partisan media (although the evidence on media effect is mixed, e.g., Levy, 2021). Media consumption captures the combined effect of farmers' inherent and acquired partisan bias, and we do not attempt to separate the two. The extremely polarized media consumption in our sample and various robustness checks supports the use of media consumption as proxies for political alignment.

We collected data from a 2019 mixed-mode survey of 471 crop farmers with over 250 acres of land in operation in Iowa, Illinois, and Minnesota. In per capita terms, the Midwest is one of the regions most affected by trade war tariffs and received the highest MFP payments

(Choi and Lim, 2022, Yu et al., 2022). The medium to large farmers we surveyed experience tangible and significant impacts of the US-China trade war, making them ideal for studying reactions to trade policies. In terms of political composition, the three states are neither extremely conservative nor liberal, and the rural voters in these states have similar voting records as rural voters nationally.[1] Furthermore, Iowa and Minnesota are battleground states. Iowa is a crucial early-voting state, and farmers in these states have strong political voices. Therefore, our study area and sample have inherent importance.

We report two main findings. First, political bias does affect economic perceptions. Farmers' perceived income loss for the year 2018 decreases by 0.46% when the conservative bias score (average=4.1 for farmers who consume some conservative media) increases by one, indicating the consumption of more conservative media such as FOX News. When the magnitude of the liberal bias score (average=-3.1 for farmers who consume some liberal media) increases by one, farmers' expected income loss decreases by 0.68% ($p<0.1$). Also, a one-point increase in conservative (liberal) bias score is associated with a 3.4% increase (3.7% decrease) in the probability of farmers perceiving the 2018 MFP payments as helpful. Second, there is little association between media consumption and farming and marketing behavior. Among the five behavior outcomes and twenty coefficients for conservative and liberal media consumption in

[1] In both the 2016 and 2020 presidential elections, Democratic presidential candidates won in Minnesota and Illinois and lost in Iowa. Minnesota and Iowa are both battleground states that are rated by (New York Times, 2017) as places that "tend to vote like the country as a whole." The 2016 Republican vote shares in IA, IL, and MN rank 22, 43, and 34, respectively. In the 2016 presidential election, the average Republican vote share in rural counties is 71% in these three states and 68% in other states. (Authors' calculation using 2016 state and county-level presidential election data from MIT Election Lab. Rural areas are defined as entirely rural counties or non-metro counties that are not adjacent to metro counties according to the USDA Rural-Urban Continuum Codes.)

2018 and 2019, only liberal media has a marginally significant impact ($p<0.1$) on pre- and at-harvest marketing in 2018 that does not survive robustness checks.

This article relates and contributes to three lines of literature. First, this study extends the literature on how trade policies (Autor et al., 2020; Che et al., 2022), including the US-China trade war (Choi & Lim, 2022; Janzen et al., 2021), impact political outcomes. The results demonstrate that the polarizing effects of trade policies may be due to partisan bias in perceptions. Second, this paper contributes to the literature on the general determinants of trade policy preference (Blonigen, 2011) and farmers' preference for protectionism in particular (Viskupič et al., 2022). We provide evidence that partisan bias affects individuals' perceptions of policy impacts. Third, we add to the literature on partisan bias in economic perceptions (e.g., Evans & Pickup, 2010) and behaviors (Gerber & Huber, 2009; McGrath, 2017). We show that the partisan bias in perception exists even when a policy directly affects individuals' economic conditions, and the bias does not extend to behaviors.

II. Conceptual Framework

Previous literature has shown that voting behavior is responsive to the economic impacts of trade shocks and MFP subsidies and that people's responses differ by prior political alignment (Choi & Lim, 2022, Janzen et al., 2021). We propose that people's perceptions of the trade war and MFP impacts differ by their political alignment (i.e., partisan bias), which can potentially explain the heterogeneous voter responses across the political spectrum. The partisan bias in perceptions may or may not translate into partisan bias in economic decisions depending on the nature of the bias.

The literature on partisan bias provides three explanations for why partisan bias exists. First, people with different political affiliations selectively consume and absorb information (Jerit & Barabas, 2012). Second, people may engage in "motivated reasoning" and process the same information differently based on their motives (Kunda, 1990; Bullock & Lenz, 2019). Third, people may engage in "cheerleading," which means they provide answers favorable to their political party without any reasoning process (Bullock & Lenz, 2019). If there is partisan bias from these three mechanisms, more conservative farmers should report lower negative impacts from tariffs and more helpfulness of MFP, while liberal bias should have the opposite effects.

Partisan bias in perceptions may result in different economic decisions. First, farmers who believe that the trade war has a larger negative impact on the profitability of soybean production (combining tariff and MFP impacts) could reduce soybean acres (Choi & Helmberger, 1993). Second, if a farmer expects a price decline, they could sell the products early by reducing storage and increasing pre-harvest sales (Kadjo et al., 2018). Finally, if a farmer believes that the trade war increases risks, they could increase the use of hedging tools such as pre-harvest sales and non-spot market sales (e.g., futures, and options, MacDonald, 2020). However, these expected behavior differences will not realize if farmers use different reasoning processes for political and economic decisions or if they are "cheerleading" for their party when reporting their beliefs and perceptions. See Appendix 3 for a more detailed discussion of these economic decisions.

III. Data and Summary Statistics

3.1 Survey

Following Dillman et al. (2014) Tailored Survey Design method, we sent mixed-mode surveys via mail and online through Qualtrics to 3,000 crop farmers over the age of 18 with at least 250 acres of cropland in Iowa (44%), Illinois (32%), and Minnesota (23%).[2] The survey asked about farmers' demographic and farm characteristics, most frequently used media sources for trade-war information, perceived farm income loss in 2018 from the trade war before MFP payments, perceived helpfulness of the first round of MFP payments in 2018, and various farming and marketing decisions. We received 722 responses (a 24.1% response rate), and 64% of the responses were via mail. After dropping respondents who did not provide expected income loss from the trade war (a main outcome of interest) and other important farm characteristics, 471 usable observations remained. Figure 1 shows the county locations of surveyed farmers' primary farm operations and county-level soybean planted acres in 2018.

[2] We selected respondents through stratified sampling, and the sample is from Dynata, a company that provides address lists. Multi-farm operations may span several counties and states, and our survey asked for the location of the primary farm. Six respondents reported that their primary farms are outside the three states. We chose 250 acres because farms with at least 260 acres represent over 70% of farmland in these three Midwestern states (USDA 2019) and represent an even larger share of agricultural commodity trade. Our sample of farms with at least 250 acres may limit the generalizability of the results to farmers with smaller operations.

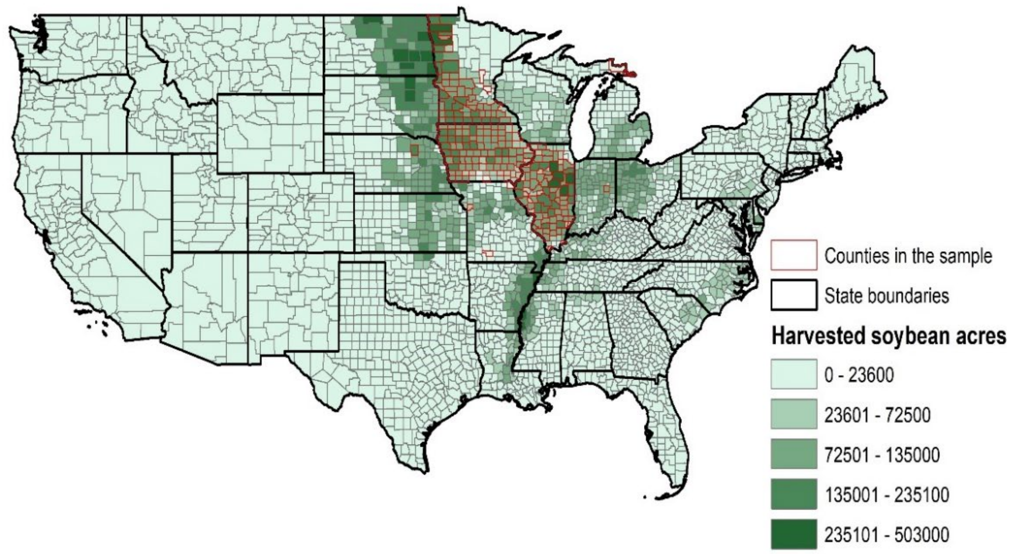

Figure 1. Counties in sample and soybean planted acres.

Notes: This figure shows the counties where the primary farms are located and the county-level soybean planted acres across the contiguous United States in 2018. There are 471 farmers in the final analysis. Though most respondents' primary farm operations are in Iowa, Illinois, and Minnesota, several respondents' primary farm operations are located in other states.

3.2 Key Variables

The key independent variable (Appendix Tables A1 and A2), media bias, comes from the open-ended question, "When seeking information about the trade disruption, what are your three most frequently used media sources?" We classify the reported media outlets into three categories—liberal, neutral, and conservative based on bias scores from Mediabiascheck.com (Appendix Table A2). The raw bias score for individual sources ranges from liberal bias (-6≤bias score<-1) to mostly neutral (-1≤bias score≤1) to right bias (1<bias score≤6). For example, CNN is classified as a liberal media based on a bias score of -2, while Fox News is classified as a

conservative media based on a bias score of five. Three farmer associations without available scores (Farm Bureau, Soybean Producers' Association, and Corn Producers' Association) have center-right bias, according to the expert opinions of farm management specialists from Iowa State University Extension. Puglisi and Snyder (2015) corroborate these expert opinions. We assign bias scores of two to the three farmer associations and conduct robustness checks by classifying them as neutral. All other farm-related sources are classified as neutral.[3]

The main conservative and liberal bias measures are continuous bias scores calculated by summing bias scores of conservative and liberal media sources separately. If an individual does not list any conservative or liberal media, the corresponding score is zero. For example, if a farmer watches FOX News (bias score = 5) and PBS (bias score = -1), and reads Wall Street Journal (bias score = 3), her cumulative bias score for conservative and liberal media would be 8 and -1, respectively. The cumulative score for liberal media is converted to be positive in regressions so that its magnitude increases with the degree of bias. Whether the respondent consumes neutral media is included as a binary control variable. We also explore alternative media bias measures, including dummy variables indicating whether the person consumes conservative or liberal media, the share of liberal or conserve media sources reported, and a definition where all farm-related information sources are coded as neutral.

The first set of outcomes we examine is farmers' perceived income loss from the trade war (before receiving MFP) and the helpfulness of the MFP payments in 2018. The perceived

---

3 Only two farm-related media sources (including the *Successful Farming* magazine, which is the most popular neutral source in the sample with a 31.5% readership [Appendix Table2]) have available bias scores, and both of them are between -1 and 1.

income loss is a categorical variable from 1 (Down more than 20%) to 9 (Up more than 20%). In the main analysis, we use interval regression (Billard & Diday, 2000) to avoid making assumptions about the mean value for each category. To gauge the accuracy of farmers' perceived income loss, we also estimate actual income loss using two alternative specifications proposed by Janzen and Hendricks (2020) and calculate the gap between actual loss and perceived loss (see Appendix 4). For this exercise, we convert the categorical variable to the mean of the upper and lower bounds that define each category.[4] The perceived helpfulness of MFP in 2018 is measured on a five-point scale and recoded to a binary variable (zero for "not at all helpful" ~ "somewhat helpful"; one for "quite helpful" and "very helpful") for the ease of presentation.

The second set of outcomes involves farmers' decisions regarding soybean storage, planting, and marketing (Appendix 3) in 2018. Farmers' soybean planting behavior is measured by the share of soybeans in total planted acreages. The how farmers changed their soybean storage on a five-point scale and recoded to a binary variable (one for "decrease storage a lot" and "decrease storage a little"; zero for "no change" ~ "increase storage a lot"). Marketing behavior includes the shares of soybeans sales using pre-harvest marketing and non-spot market sales (0~1).

---

4 We code scale 1 (*up more than 20%*) as -25%, scale 2 (*up 10-20%*) as -15%, scale 3 (*up 5-10%*) as -7.5%, scale 4 (*up less than 5%*) as -2.5%, scale 5 (*no change*) as 0%, scale 6 (*down less than 5%*) as 2.5%, scale 7 (*down 5-10%*) as 7.5%, scale 8 (*down 10-20%*) as 15%, and scale 9 (*down more than 20%*) as 25%. We conduct robustness checks with alternative mean value assumptions (Appendix Table A5).

3.3 Summary Statistics

Table A2 presents the media bias score by media source and the percent of respondents consuming that media. Farmers sought information about the US-China trade war mainly from conservative (57.7%, with a mean score of 4.1 among conservative media consumers), followed by neutral information sources (51.5%) and liberal media (31.5%, with a mean score of -3.1 among liberal media consumers). Among the 471 participants, only 49 (10.4%) use liberal and conservative media simultaneously. The segregation of audiences supports our interpretation of media consumption as a proxy for political bias.

Tables 1 and A5 present summary statistics for the outcome and independent variables. The cumulative bias scores reported in Table 1 are sample averages, with zero representing not consuming conservative/liberal media and the liberal bias reserved from negative to positive. After we convert the scale variable to the mean of the upper and lower bounds that define each category, the average perceived income loss is 14.4%. The estimated average actual loss is 11.2% or 16.7%, depending on the calculation method. The average perception of whether MFP is helpful is 3.6 on a five-point scale from 1 to 5, with 45.3% of farmers saying it is "quite helpful" or "very helpful."

Table 1. Summary Statistics

	Mean	SD	Min	Max
Cumulative Media Bias Scores				
Conservative	2.36	2.57	0.00	10.00
Liberal (in absolute value)	0.59	1.33	0.00	9.00
Beliefs				
Expected income loss in 2018 (9:> 20%; 5=0%; 1: <-20%)	7.68	1.52	1	9
Expected income loss in 2018 (%)	14.38	9.66	-25	25

MFP helpfulness in 2018 (1=Not at all ~ 5=Very helpful)	3.61	1.11	1	5
Behaviors				
Soybean storage 2018 (1=Decrease a lot ~ 5=Increase a lot)	3.39	0.93	1.00	5.00
Share of soybeans planted in 2018	0.47	0.13	0.1	1
Share of corn planted in 2018	0.54	0.13	0.1	1
Share of soybeans sold in non-spot market in 2018	0.46	0.21	0	1
Share of soybeans sold pre- or at-harvest in 2018	0.46	0.29	0	1
Control Variables				
Consume neutral media (0=no; 1=yes)	0.51	0.50	0.00	1.00
Soybean production in 2018 (Bushel)	29,484	24,933	2,283	266,013
Corn production in 2018 (Bushel)	117,513	109,365	9,192	1,212,993
Share of land rented	0.6	0.28	0	1
Non-irrigated land cash rent per acre ($ per acre)	210.4	42.84	42	289
Age	60.52	10.53	27	85
Attend some college or above (0=no; 1=yes)	0.36	0.48	0	1
Male (0=no; 1=yes)	0.97	0.17	0	1
Willingness to take risks (1~7)	4.47	1.27	1	7
Have livestock on farm (0=no; 1=yes)	0.38	0.49	0	1
Have off-farm job (0=no; 1=yes)	0.69	0.46	0	1
Farm income ($)	657,383	482,649	30,000	1,500,000
Ineligible for MFP (Income above $900,000)	0.21	0.40	0	1
Surveyed after 05/2019 (0=no; 1=yes)	0.61	0.10	0	1
County Republican vote share	656,147	482,881	30,000	1,500,000

Notes: We received 722 valid responses and dropped observations with missing answers to the main question on farmers' expected income loss from trade disruptions and additional control variables, resulting in 471 observations.

In 2018, respondents produced an average of 29 thousand bushels of soybeans and 117 thousand bushels of corn. Most respondents (66.4%) report that their soybean storage stayed the same or decreased in 2018. Farmers sold an average of 46.4% of their soybeans pre- and at-harvest and sold 46.1% of soybeans in the non-spot market, including futures, options, and other grain contracts.

IV. Empirical Methods

4.1 Econometric Model

The econometric model we use to measure the association between the consumption of partisan media and economic perceptions and farming behavior is:

$$Y_{icd} = \alpha_0 + \beta_0 Cons_{icd} + \beta_1 Lib_{icd} + \gamma Z_{icd} + FE_d + \varepsilon_{icd}, \quad (1)$$

where Y_{ics} denotes the outcome of interest; $i, c,$ and d are the indexes for individuals, counties, and congressional districts, respectively; and, $Cons_{ics}\ and\ Lib_{ics}$ represent farmer i's consumption of conservative and liberal media bias measures as explained in Section 3.2.

To alleviate the concern of omitted-variable bias, we include a rich set of control variables, Z_{ics}, which include whether the farmer consumes neutral media sources, farmer demographic characteristics, farm characteristics, and others. Demographic variables include farmers' income, age, education, and gender. Farm characteristics include 2018 soybean and corn production (calculated using farmers' 2018 planted acreage and county-level yield), whether the farmer has livestock, whether the farmer has an off-farm job, and the cash rent for that farm. We estimate cash rent by multiplying the county-level cash rent for non-irrigated cropland by the share of rented land. The local political environment is controlled using the share of Republican votes for each county in the 2016 presidential election. We also control for whether the farmer is eligible for the first round of MFP payments, measured by whether the farmer has an income below \$900,000 (USDA, 2018). The model includes congressional district fixed effects, FE_d, to capture time-invariant differences across locations. Due to the limitation of sample size, including fixed effects at finer geographical levels will absorb most of the variation. The error term (ε_{icd}) is clustered at the county level to allow for error correlation between observations within a county.

The outcomes include both continuous and categorical variables, and we choose econometric models accordingly. We use interval regression (Billard & Diday, 2000) for categorical variables with known cutoff points (perceived income loss), the probit model for binary variables (MFP helpfulness and the change in storage), and Ordinary Least Square (OLS) regression for continuous variables (all other variables). Average marginal effects are reported for Probit and models.

V. Results

5.1 Perceived Economic Conditions

Table 2 shows farmers who produce more soybeans perceive more income loss (column 1) and are more likely to believe that MFP payments are helpful (column 4) [5]. These results are expected considering that both China's retaliatory tariffs and the first round of MFP payments target soybean farmers. This is consistent with previous studies showing that people's political behaviors respond to trade shocks and MFP payments. The results discussed below show that political biases also affect people's expectations after controlling for economic fundamentals.

Table 2. Media Consumption and Farmers' Perceived Income Loss, the Gaps between Perceived and Actual Income Loss, and Perceived MFP Payment Helpfulness

5 See Appendix Figure A1 and A2 for a more detailed illustration of these results using Lowess graphs.

	Income Loss	Gap Method 1	Gap Method 2	MFP Helpfulness
	(1)	(2)	(3)	(4)
Conservative	-0.455**	-0.396	-0.492*	0.034***
	(0.206)	(0.251)	(0.253)	(0.009)
Liberal	0.676*	0.916*	0.911*	-0.037**
	(0.407)	(0.484)	(0.464)	(0.016)
Neutral	1.339	0.901	0.978	-0.041
	(1.070)	(1.276)	(1.282)	(0.045)
Ln(soybean production)	2.212*	-8.635***	-9.058***	0.160***
	(1.266)	(1.810)	(1.914)	(0.052)
Ln(corn production)	-1.451	-10.018***	-4.402**	-0.102*
	(1.332)	(1.628)	(1.732)	(0.055)
Age	-0.068	-0.031	-0.053	-0.006**
	(0.056)	(0.070)	(0.068)	(0.002)
College	0.338	-0.521	-0.834	-0.071
	(1.137)	(1.433)	(1.438)	(0.048)
Male	-1.780	-2.452	-2.520	0.238*
	(3.118)	(3.177)	(3.137)	(0.136)
Risk tolerance	-0.512	-0.828*	-0.846*	0.021
	(0.426)	(0.486)	(0.500)	(0.018)
Ln(farm income)	-0.838	24.508***	18.758***	0.020
	(0.778)	(1.404)	(1.560)	(0.032)
Have livestock	-1.786	-3.452**	-3.382**	0.023
	(1.102)	(1.521)	(1.519)	(0.047)
Have off-farm income	0.610	0.398	0.430	0.070
	(1.149)	(1.346)	(1.336)	(0.049)
Ln(cash rent)	-0.006	-0.007	-0.007	-0.000
	(0.009)	(0.011)	(0.010)	(0.000)
Ineligible for MFP (Income above	2.719	-7.135***	-6.438***	-0.153**
$900,000)	(1.813)	(2.270)	(2.249)	(0.077)
County Republican vote	7.170	13.686**	10.155*	-0.008
share in 2016	(5.980)	(6.043)	(6.128)	(0.249)
Congressional Dist. FE	Yes	Yes	Yes	Yes
N	471	471	471	461

Notes: This table presents the estimation results of the association between media consumption and farmers' perceived income loss and the helpfulness of MFP payments. Column (1) presents the interval regression results on perceived income loss. Columns (2) and (3) present the OLS results for the gap between expected and actual income loss calculated using two alternative methods (Appendix 2.) Column (4) shows the marginal effects from a Probit model estimating the association between media consumption and the perceived helpfulness of MFP. We include congressional-district fixed effects in all specifications. Standard errors are clustered at the county level for OLS regressions. Robust standard errors are reported for other estimates. *, **, and *** denote significance levels at $p<0.1$, $p<0.05$, and $p<0.01$, respectively.

The main results in Table 2 are how the consumption of partisan media is associated with farmers' perceived income loss and the helpfulness of MFP payments. In Column (1), interval regression results show that a one-point increase in the conservative bias score leads to 0.46% lower expected income loss. For liberal media consumption, Column (1) shows that a one-point increase in liberal media bias score is associated with a 0.68% decrease in perceived income loss. Back-of-the-envelope calculations show that the average consumer of conservative (liberal) media perceives income loss to be 1.9% (2.1%) percentage points lower (higher), compared to the average perceived income loss of 14.4%.[6] The implied difference in perceived income loss between the average consumers of conservative and liberal media sources (with and without consuming neutral media) is 4.0% of the total income, which is equivalent to about $26,000 for the average farm with an income of $657,147 (Table 1). The results on the gap between actual and perceived income loss (Table 2, Columns (2) and (3)) show that conservative bias changes the difference in the positive direction, consistent with conservative bias lowering expected income loss. The calculation of the actual-perceived income gaps involves assumptions on the mean values of income intervals reported in the survey. Robustness checks using alternative

6 These numbers are estimated by multiplying the regression coefficient for conservative (liberal) bias by the average bias score faced by consumers of conservative (liberal) farmers (Appendix Table 1).

mean value assumptions for income loss intervals show similar qualitative results with some changes in effect size (Appendix Table A4).

Results in Table 2, Column (6) indicate that a one-point increase in conservative bias score increases the probability of farmers considering MFP payments helpful by 3.4%. In comparison, a one-point decrease in liberal bias score decreases the possibility of viewing MFP payments as helpful by 3.8%. Regarding whether they find MFP to be helpful, the average consumers of conservative and liberal media differ by 25.7 percentage points. Overall, the results in Table 2 show that, controlling for economic fundamentals, farmers with conservative political alignment are more optimistic about the trade war's impacts on their income, while those with liberal alignment seem to be more pessimistic. These findings show that partisan bias in perceptions exists even when substantial financial interests are at stake.

5.2 Media and Behavior

Table 3 and A3 present results about the association between media consumption and farmers' economic behavior in 2018 and 2019, respectively. The coefficients for control variables, when statistically significant, have the expected signs. For example, more soybean (corn) production in previous years (2013~2017) leads to a significantly higher share of land allocated to soybeans (corn) (Table 3, Columns (2) and (3)), which shows the persistence in crop choice across years. As expected, farmers with higher risk tolerance are more likely to continue to produce affected crops (Table 3, Column (2)).

Table 3. Media Consumption and Farmers' Behavior

	Soybean storage	Share of soybeans planted	Share of corn planted	Soybeans sold pre- and at-harvest	Soybean sold on non-spot markets
	(1)	(2)	(3)	(4)	(6)
Conservative	-0.003	0.001	0.000	0.004	-0.004
	(0.005)	(0.002)	(0.001)	(0.005)	(0.003)
Liberal	0.004	0.001	0.002	0.017*	0.009
	(0.008)	(0.004)	(0.004)	(0.010)	(0.008)
Neutral	-0.051**	-0.007	-0.006	0.030	0.001
	(0.025)	(0.010)	(0.010)	(0.026)	(0.019)
Ln(soybean production)	0.032	0.191***	-0.218***	0.012	0.027
	(0.033)	(0.012)	(0.011)	(0.034)	(0.026)
Ln(corn production)	-0.058*	-0.190***	0.215***	0.027	0.015
	(0.032)	(0.012)	(0.013)	(0.034)	(0.027)
Age	0.001	0.001	0.001	-0.003**	-0.001
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
College	0.005	-0.009	-0.011	-0.036	0.005
	(0.028)	(0.009)	(0.009)	(0.029)	(0.022)
Male	-[a]	-0.011	0.007	-0.133	0.064
	-[a]	(0.015)	(0.014)	(0.083)	(0.041)
Risk tolerance	0.009	0.007**	0.006*	0.023*	0.011
	(0.009)	(0.003)	(0.003)	(0.012)	(0.010)
Ln(farm income)	0.011	-0.000	0.000	0.014	-0.003
	(0.022)	(0.003)	(0.004)	(0.022)	(0.013)
Have livestock	0.022	-0.006	-0.003	0.004	-0.018
	(0.027)	(0.010)	(0.008)	(0.032)	(0.024)
Have off-farm income	-0.003	-0.005	-0.001	0.077***	0.025
	(0.028)	(0.011)	(0.009)	(0.027)	(0.020)
Ln(cash rent)	-0.000	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ineligible for MFP	0.048	-0.003	0.006	0.024	0.007
(Income above $900,000)	(0.043)	(0.019)	(0.015)	(0.044)	(0.030)
County Republican vote	-0.007	0.006	-0.005	-0.086	0.031
share in 2016	(0.136)	(0.035)	(0.034)	(0.150)	(0.112)
Congressional district FE	Yes	Yes	Yes	Yes	Yes
N	414	471	471	471	471

Notes: This table presents the association between media consumption and farmers' soybean storage, soybean and corn planting, and marketing behavior in 2018. Column (1) presents marginal effects from a Probit model on whether the farmer decreases soybean storage. Columns (2) ~ (5) are estimated with OLS. We include congressional-district fixed effects in all specifications and cluster standard errors at the county level. Standard errors are in parentheses. *, **, and *** denote significance levels at p<0.1, p<0.05, and p<0.01, respectively.

a. coefficient dropped because of perfect collinearity.

However, we find only one coefficient (liberal bias on the pre- and at- harvest marketing of soybeans) that is marginally significant (p<0.1) among 20 coefficients of interest in Table 3 and A3. Later, we will show that this statistically significant result does not survive any of the robustness checks, hence likely a statistical fluke. Though the lack of statistical power could cause noisy estimates on individual coefficients, the absence of statistically significant results in almost all behavioral outcomes suggests that political alignment has a weak, if not non-existent, association with economic behavior. When examining the confidence intervals, we find that the effects of conservative and liberal media biases are practically small for most of the outcomes. Take the estimated impact of conservative media consumption on the share of soybean planted in 2018 (arguably the most obvious behavior response) as an example (Table 3 Column (2)). The upper bound of the 95% confidence interval represents a 0.5% increase in the percent of soybean planted when the conservative bias score increases by one. This upper-bound estimate implies that the average consumer of conservative media (with an average conservative bias score of 4.1) will only plant 2% more soybeans, which is modest relative to the sample average of 47% soybeans planted (Table 1).

5.4 Additional Robustness Checks

We check the robustness of our results in several ways. We first check the robustness of our results to alternative media bias measures, including 1) whether the farmer consumes conservative or liberal media; 2) the share of conservative and liberal media sources consumed; 3) a more restrictive list of conservative media sources with three expert-determined conservative sources coded as neutral. Table 4, Panels A~C show that the main findings remain robust—media bias measures have qualitatively similar associations with perceptions (Columns (1)~(3)), and none of the alternative media bias measures have a statistically significant association with behavioral variables (Table 4, Columns (4)~(7)).

Table 4. Robustness checks

	Income Loss	Gap method 2	MFP Helpfulness	Storage	Share planted	Sold pre- and at-harvest	Sold on non-spot markets
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Media bias measure: Dummy							
Conservative	-1.419	-1.782	0.158***	-0.015	0.005	-0.010	-0.022
	(1.109)	(1.350)	(0.046)	(0.026)	(0.008)	(0.030)	(0.019)
Liberal	3.232**	3.141*	-0.110*	0.036	0.002	0.029	0.027
	(1.384)	(1.751)	(0.057)	(0.029)	(0.013)	(0.035)	(0.028)
Panel B: Media bias measure: Share							
Conservative	-0.946	-1.793	0.195***	-0.022	0.010	-0.003	0.012
	(1.626)	(2.093)	(0.069)	(0.036)	(0.009)	(0.043)	(0.028)
Liberal	5.110**	5.046*	-0.134	0.045	0.016	0.042	0.063
	(2.268)	(2.729)	(0.096)	(0.045)	(0.024)	(0.059)	(0.045)
Panel C: Media bias measure: Farm-related as neutral							
Conservative	-0.459**	-0.475*	0.032***	-0.005	0.001	0.008	-0.003
	(0.221)	(0.278)	(0.009)	(0.005)	(0.002)	(0.005)	(0.003)
Liberal	0.658	0.893*	-0.036**	0.006	0.001	0.016	0.008
	(0.408)	(0.469)	(0.017)	(0.008)	(0.004)	(0.010)	(0.008)
Panel D: Drop observation with both conservative and liberal media consumption							
Conservative	-0.470**	-0.542**	0.037***	-0.007	0.001	0.002	-0.006
	(0.219)	(0.268)	(0.009)	(0.005)	(0.002)	(0.006)	(0.004)
Liberal	0.798	0.792	-0.029	-0.010	0.003	0.015	0.008
	(0.543)	(0.651)	(0.022)	(0.010)	(0.006)	(0.013)	(0.010)

Panel E: Using weighted regression to correct for conservative/liberal imbalance							
Conservative	-0.468**	-0.488*	0.034***	-0.002	0.001	0.005	-0.004
	(0.223)	(0.257)	(0.009)	(0.005)	(0.002)	(0.005)	(0.003)
Liberal	0.680	0.870*	-0.035**	0.000	0.001	0.017*	0.009
	(0.438)	(0.464)	(0.016)	(0.008)	(0.003)	(0.010)	(0.008)

Notes: This table reports robustness checks using alternative media definitions and sampling criteria. Panel A measures media bias using dummy variables indicating whether the farmer consumes conservative (liberal) media sources. Panel B measures media bias using the share of conservative and liberal media sources in the total number of media sources. Panel C code farm-related media sources (Farm Bureau and Soybean/corn Associations) as neutral media. Panel D drops farmers who consume both conservative and liberal media who cannot be easily classified as conservative or liberal. Panel E uses the sample in Panel D and weights observations using the ratio between nationwide rural Republican (Democratic) vote share and the number of farmers consuming Conservative (Liberal) media sources. *, **, and *** denote significance levels at $p<0.1$, $p<0.05$, and $p<0.01$, respectively.

Second, we attempt to address the concern that biased media consumption may be an inaccurate proxy for partisan alignment. We argue that if a farmer consumes only conservative or liberal media sources (allowing for neutral media consumption), then they can be reliably identified as having conservative or liberal political alignment. Therefore, we drop farmers who consume both conservative and liberal media sources to reduce the measurement error. Results (Table 4, Panel D) show that all main results are qualitatively stable. Importantly, even with the arguably more accurate measure of partisan bias in this restricted sample, media consumption still has no statistically significant effects on behaviors.

Third, we use weighted regressions so that our results can better generalize to the rural population. While the rural Midwest has a similar political composition as rural areas nationwide, farmers in our survey seem to be somewhat more conservative than the rural population in the nation. The ratio between farmers who consume conservative media only and liberal media only is 4.7:1. This is higher than the Republican-to-Democrat ratio of 3.5:1 in rural areas nationally.[7] This is not surprising because a poll has shown that 85% of farmers intended to vote for Trump in the 2020 presidential election (Bunge, 2020). To confirm that our results can be generalized to the rural population, we assign farmers who consume conservative media only a weight that equals the ratio between the share of conservative-only media consumers in the sample and the national rural Republican vote share. A similar weight is calculated for farmers who only consume liberal media. We remove farmers who consume mixed media from this analysis. The weighted regression results (Table 4, Panel E) are similar to the main results.

VI. Discussion and Conclusions

Based on a survey of 471 farmers in three Midwestern states, we investigate the correlation between the consumption of conservative and liberal media and farmers' perceptions and economic behaviors with respect to the US-China trade war. Though we base our results on media consumption, we argue that the results in this study are strongly indicative of the relationships between political alignments and these perceptions and behaviors.

We find that farmers' perceptions of economic loss and MFP helpfulness are determined by economic fundamentals as expected: the more soybean they produce, the higher trade impacts and MFP helpfulness they perceive. However, we also find that after controlling for economic fundamentals, the consumption of media with conservative (liberal) bias is associated with a reduction (increase) in farmers' perceived income loss from the trade war and an increase (decrease) in perceived helpfulness of MFP payments. While previous studies have found similar

7 Authors' calculation using 2016 state and county-level presidential election data from MIT Election Lab. Rural areas are defined as entirely rural counties or non-metro counties that are not adjacent to metro counties according to the USDA Rural-Urban Continuum Codes.

biases for populations with little to no financial stake in their perceptions, our findings suggest that the partisan bias persists even when substantial financial interest is involved.

In contrast to the strong correlation between media consumption and farmers' perceptions, we find little correlation between partisan media consumption and economic decisions. Though we cannot completely rule out partisan biases in behaviors, the absence of statistically significant effects in almost all behaviors studied suggests that political alignments have weak effects, if any, on economic behaviors. The inconsistency between stated perceptions and behavior here adds weight to the argument that survey responses about economic perceptions are subject to cheerleading.

This study has several limitations, and thus future studies can improve upon ours. This study relies on the effects of media consumption to infer the effects of political attitudes. As a result, the relationships we discover are qualitative. Given the imperfect correlation between media consumption and political attitudes, the magnitude of media effects is likely smaller than the underlying effects of political attitudes. In addition, we cannot separately identify the political biases that already exist when people choose media sources and additional biases created from media consumption. The results in this paper should be interpreted as the combined effects of the pre-existing and media-induced biases.

References

Anderson, Kym, Gordon Rausser, and Johan Swinnen. 2013. “Political Economy of Public Policies: Insights from Distortions to Agricultural and Food Markets.” *Journal of Economic Literature*, 51(2): 423-77.

Autor, David, David Dorn, Gordon Hanson, and Kaveh Majlesi. 2020. “Importing Political Polarization? The Electoral Consequences of Rising Trade Exposure.” *American Economic Review*, *110*(10), 3139-3183.

Balistreri, Edward, Wendong Zhang, and John Beghin. 2020. “The State-level Burden of the Trade War: Interactions between the Market Facilitation Program and Tariffs”, *Agricultural Policy Review*, Iowa State University Center for Agricultural and Rural Development (CARD), Winter 2020.

Billard, Lynne, and Edwin Diday. 2000. “Regression Analysis for Interval-valued Data.” In *Data Analysis, Classification, and Related Methods*. Berlin: Springer, 369-374.

Blonigen, B.A., 2011. ‘Revisiting the Evidence on Trade Policy Preferences.” *Journal of International Economics*, 85(1), pp.129-135.

Bown, Chad P. and Melina Kolb. 2021. “Trump’s Trade War Timeline: An Up-to-Date Guide.” Washington, DC: Peterson Institute for International Economics. Retrieved June 22, 2021 (https://www.piie.com/blogs/trade-investment-policy-watch/trump-trade-war-china-date-guide).

Bullock, John, and Gabriel Lenz. 2019. “Partisan Bias in Surveys.” *Annual Review of Political Science* 22: 325-42.

Bunge, Jacob 2020. “Farmers Stick with Trump, Despite Trade-War Pain” *The Wall Street Journal* 2020.

Che, Yi, Yi Lu, Justin R. Pierce, Peter K. Schott, and Zhigang Tao. 2022. “Did Trade Liberalization with China Influence US Elections?” *Journal of International Economics*, *139*, 103652.

Choi, Jung-Sup, and Peter G. Helmberger. 1993. “Acreage Response, Expected Price Functions, and Endogenous Price Expectations.” *Journal of Agricultural and Resource Economics* 37-46.

Choi, Jaerim, and Sunghun Lim. 2022. “Tariffs, Agricultural Subsidies, and the 2020 US Presidential Election.” *American Journal of Agricultural Economics*.

Dillman, D. A., Smyth, J. D., & Christian, L. M. 2014. “Internet, Phone, Mail, and Mixed-mode Surveys: The Tailored Design Method.” John Wiley & Sons.

Evans, Geoffrey, and Mark Pickup. 2010. “Reversing the Causal Arrow: The Political Conditioning of Economic Perceptions in the 2000–2004 US Presidential Election Cycle.” *The Journal of Politics* 72(4): 1236-1251.

Fajgelbaum, Pablo D., Pinelopi K. Goldberg, Patrick J. Kennedy, and Amit K. Khandelwal. 2020. “The Return to Protectionism.” *The Quarterly Journal of Economics* 135(1): 1-55.

Fetzer, Thiemo, and Carlo Schwarz. 2021. “Tariffs and Politics: Evidence from Trump’s Trade Wars.” *The Economic Journal*, *131*(636), 1717-1741.

Gerber, Alan S., and Gregory A. Huber. 2009. "Partisanship and Economic Behavior: Do Partisan Differences in Economic Forecasts Predict Real Economic Behavior?" *American Political Science Review* 103(3): 407-26.

Gerber, Alan S., and Gregory A. Huber. 2010. "Partisanship, Political Control, and Economic Assessments." *American Journal of Political Science* 54(1): 153-73.

Grant, Jason H., Shawn Arita, Charlotte Emlinger, Robert Johansson, and Chaoping Xie. 2021. "Agricultural Exports and Retaliatory Trade Actions: An Empirical Assessment of the 2018/2019 Trade Conflict." *Applied Economic Perspectives and Policy*, *43*(2), 619-640.

Janzen, Joseph P., and Nathan P. Hendricks. 2020. "Are Farmers Made Whole by Trade Aid?" *Applied Economic Perspectives and Policy* 42(2): 205-226.

Janzen, Joseph P., Trey Malone, K. Aleks Schaefer, and Daniel P. Scheitrum (2021).. "Political Returns to Ad hoc Farm Payments?." *Applied Economic Perspectives and Policy*.

Jerit, Jennifer, and Yangzi Zhao. 2020. "Political Misinformation." *Annual Review of Political Science* 23: 77-94.

Kadjo, Didier, Jacob Ricker-Gilbert, Tahirou Abdoulaye, Gerald Shively, and Mohamed N. Baco. 2018. "Storage Losses, Liquidity Constraints, and Maize Storage Decisions in Benin." *Agricultural Economics* 49(4): 435-454.

Kunda, Ziva .1990. "The Case for Motivated Reasoning." *Psychological Bulletin* 108(3): 480.

Levy, R. E. 2021. "Social media, news consumption, and polarization: Evidence from a field experiment." *American Economic Review*, *111*(3), 831-870.

Li, Minghao, Edward J. Balistreri, and Wendong Zhang. 2020. "The US–China Trade War: Tariff Data and General Equilibrium Analysis." *Journal of Asian Economics* 69: 101216.

MacDonald, James M. 2020. "Corn and Soybean Farmers Combine Futures, Options, and Marketing Contracts to Manage Financial Risks." Washington, DC: United States Department of Agriculture Economic Research Service.

McGrath, Mary. 2017. "Economic Behavior and the Partisan Perceptual Screen." *Quarterly Journal of Political Science* 11(4): 363-83.

New York Times. 2017. 2016 Presidential Election Results. https://www.nytimes.com/elections/2016/results/president

Prior, M. 2013. "Media and Political Polarization." *Annual Review of Political Science* 16: 101-127.

Puglisi, Riccardo, and James M. Snyder Jr. 2015. "The Balanced US Press." *Journal of the European Economic Association*, *13*(2), 240-264.

Strömbäck, Jesper, Michael Karlsson, and David Nicolas Hopmann. 2012. "Determinants of News Content: Comparing Journalists' Perceptions of the Normative and Actual Impact of Different Event Properties when Deciding What's News." *Journalism Studies*, *13*(5-6), 718-728.

USDA. 2018. Market Facilitation Program (MFP) Fact Sheet.

https://www.fsa.usda.gov/Assets/USDA-FSA-Public/usdafiles/FactSheets/2018/Market_Facilitation_Program_Fact_Sheet_September_2018C.pdf

USDA. 2019. Ag Census 2017, Volume 1, Chapter 2, pp350

https://www.nass.usda.gov/Publications/AgCensus/2017/Full_Report/Volume_1,_Chapter_2_US_State_Level/st99_2_0008_0008.pdf

USDA National Agricultural Statistics Services (NASS). (2020). Data accessed from https://www.nass.usda.gov/Quick_Stats/index.php.

Viskupič, Filip, Evren Celik Wiltse, and David L. Wiltse. 2022. "Pocketbook versus Identity? Farmers' Attitudes towards International Trade." *The Social Science Journal*, 1-11.

Wilson, Mike. 2020. "Survey: Farmer Support for Trump is Overwhelming." Decatur: Farm Futures. Retrieved June 22, 2021 (https://www.farmprogress.com/farm-policy/survey-farmer-support-trump-overwhelming).

Wlezien, Christopher, Mark Franklin, and Daniel Twiggs. 1997. "Economic Perceptions and Vote Choice: Disentangling the Endogeneity." *Political Behavior* 19(1): 7-17.

Yu, J., N.B. Villoria, and N.P. Hendricks. 2022. "The incidence of foreign market tariffs on farmland rental rates" Food Policy 11: 1023

Appendix 1. Additional Tables

Table A1. Selected Survey Questions for Key Variables

Variables	Question	Choices
Media consumption	When seeking information about the trade disruption, what are your three most frequently used media sources?	Open-ended
Perceived income loss	*Before receiving trade assistance from the USDA*, to what extent do you think your farm's net income in 2018 was affected by the trade disruptions?	1 (Up more than 20%) to 9 (Down more than 20%)
Perceived MFP helpfulness	How helpful do you think President Trump's $12 billion trade relief plan will be to your farm?	1 (Not at all helpful) to 5 (Very helpful)
Soybean storage	How did the trade disruption affect your soybean storage in 2018? How will the trade disruption change your 2019 soybean storage plan compared to that of 2018?	1 (Decrease a lot) to 5 (Increase a lot)
Crop planting	On average, what percentage of corn, soybean, and other crops did you plant between 2013 and 2017? What about in 2018? What are your [cropping] plans for 2019?	Continuous variable from 0–1
Pre-, at-, or post-harvest marketing	From 2013 to 2017, what percentage of your soybean harvest did you market pre-harvest, at harvest, and post-harvest? What about in 2018? What are your plans for 2019?	Continuous variable from 0–1
Spot or non-spot markets	From 2013 to 2017, what percentage of your soybean crop did you market using the following tools? What about in 2018? What is your plan for 2019?	Continuous variable from 0–1

Notes: The questionnaire has 39 questions in total. This table lists the questions and choices for questions related to farmers' media consumption, perception, and knowledge related to the trade war.

Table A2. Summary Statistics of Farmers' frequently used media sources for trade war information.

Category	Media Source	Bias Score	% Farmers Using The Source
Conservative	Farm Bureau	2[a]	32.8%
	Fox News	5	28.7%
	National State Corn Growers	2[a]	1.5%
	National State Soybean Association	2[a]	0.4%
	WSJ	3	0.2%
	Cedar Rapids Gazette	1.8	7.7%
	All conservative	4.1	57.7%
Liberal	CNN	-3.5	10.9%
	NPR	-1.5	2.6%
	CBS	-1.5	2.1%
	NBC	-2	1.7%
	MSNBC	-4	1.5%
	Bloomberg	-1	1.3%
	PBS	-1	1.3%
	CNBC	-1.8	0.6%
	ABC	-1.8	0.4%
	All liberal	-3.1	19.1%
Neutral	Successful Farming		31.5%
	Extension		18.9%
	Farm Magazines		3.8%
	Farm Journal		3.4%
	Ag Web	-0.1	3.0%
	DTN	-0.1	2.6%
	Wallaces Farmer		1.5%
	Iowa Farmer Today		1.3%
	Pro Farmer		1.3%
	Agri-talk Radio		1.1%
	Roach Ag		0.9%
	Progressive Farmer		0.4%
	Linder Farmer Network		0.4%
	All neutral		51.5%

Notes: This table summarizes media bias scores and percent of farmers in the sample consuming each source. Most bias scores are from mediabiasfactcheck.com, which ranges from -6 to -1 denoting Left and 1 to 6 denoting Right. The bias scores with superscript a are assigned by expert opinion. The score for all conservative, all liberal, and all neutral sources are the average cumulative bias score among farmers who consume at least one source in the respective categories.

Table A3. Media Consumption and Farmers' Planned Behaviors in 2019

-	Soybean storage	Share of soybeans planted	Share of corn planted	Soybeans sold pre- and at-harvest	Soybean sold on non-spot markets
	(1)	(2)	(3)	(4)	(6)
Conservative	-0.026	-0.001	-0.001	0.004	-0.004
	(0.032)	(0.003)	(0.003)	(0.004)	(0.003)
Liberal	0.055	-0.003	0.007	0.010	0.004
	(0.061)	(0.006)	(0.005)	(0.010)	(0.007)
N	414	470	470	470	470

Notes: This table presents the impact of media exposure on farmers' soybean storage, soybean and corn planting behavior, and marketing behavior in 2018. Column (1) presents marginal effects estimated with Probit, and we estimate columns (2)–(6) with OLS. We include control variables in the main analysis and an additional variable for whether the survey was received after May 5, 2019, when a new round of US tariffs was threatened. We include Congressional-district fixed effects in all specifications and cluster standard errors at the county level. Standard errors are in parentheses. *, **, and *** denote significance levels at p<0.1, p<0.05, and p<0.01 level, respectively.

Table A4. Alternative mean values for top and bottom perceived income loss categories.

	Gap method 1	Gap method 2
	(1)	(2)
Panel A: Bottom and top categories codes as -20% and 20%		
Conservative	-0.536**	-0.626***
	(0.248)	(0.239)
Liberal	0.535	0.542
	(0.386)	(0.363)
Panel B: Bottom and top categories codes as -30% and 30%		
Conservative	-0.808**	-0.898***
	(0.311)	(0.304)
Liberal	0.678	0.684
	(0.556)	(0.538)
N	471	471

Notes: The table reports robustness checks for the actual-perceive income gap measures, which depend on assumptions about the mean values of extreme income change categories. The mean values for the bottom and top categories are set to +/- 20% and 30% instead of the +/- 25% in the main analysis (Table 2). Model specification and control variables are the same as in the main analysis. Standard errors are in parentheses. *, **, and *** denote significance levels at p<0.1, p<0.05, and p<0.01 level, respectively.

Appendix 2. Additional Figures

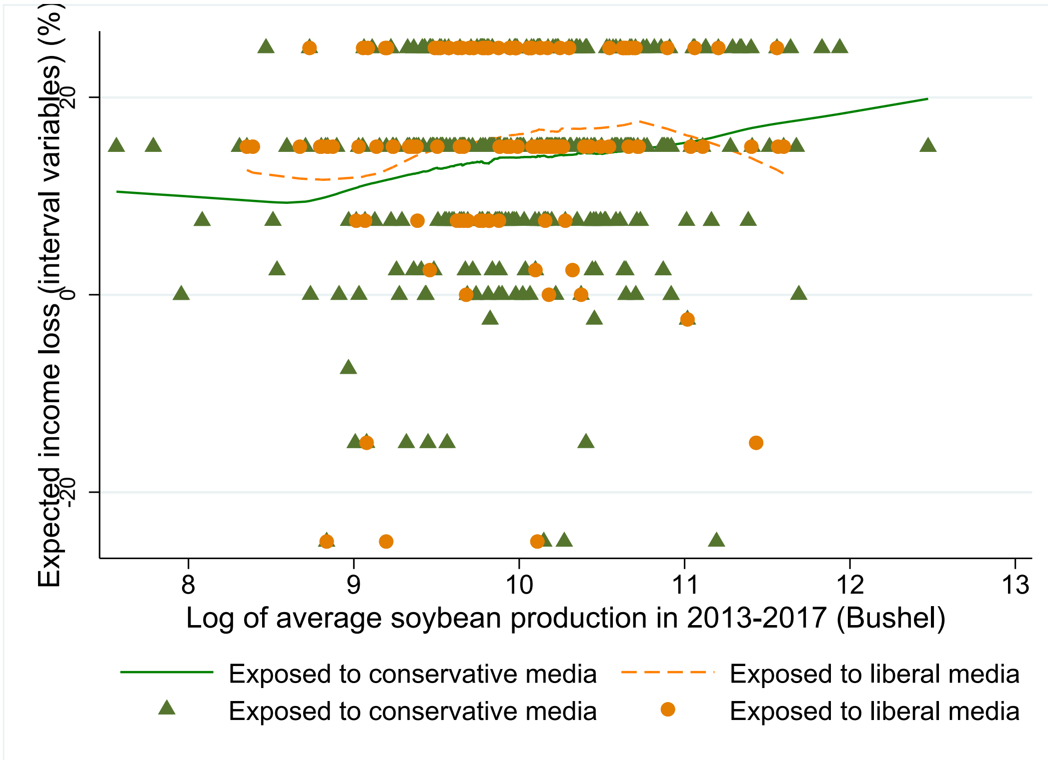

Figure A1. Average soybean production in 2013-2017 and expected income loss.

Figure A1.1 shows that for most levels of soybean production, farmers who consume liberal media have a higher expected income loss than farmers who are conservative media consumers.

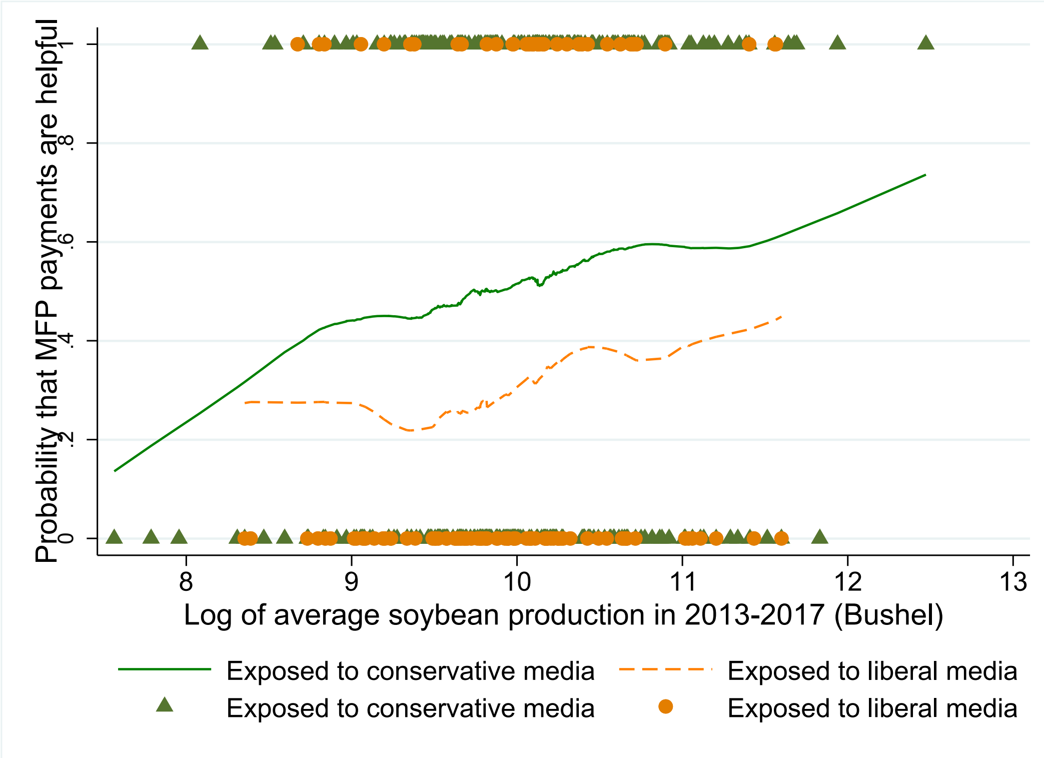

Figure A2. Average soybean production in 2013-2017 and the probability of perceiving MFP payments as helpful.

Figure A1.2 shows that given the same level of soybean production, farmers exposed to conservative media are more likely to believe that MFP payments are helpful than farmers exposed to liberal media. Furthermore, farmers with more soybean production express higher levels of expected income loss and more helpfulness of MFP, which is expected since both China's retaliatory tariffs and MFP payments target soybean.

Appendix 3: An introduction to crop planting, storage, and marketing decisions

In this appendix, we briefly explained farmers' decisions regarding planting, storage, and the usage of crop marketing tools. The purpose of this appendix is to concretely show that these decisions, to various degrees of certainty, can be affected by farmers' outlook on downward price risks.

1. Planting corn versus soybeans

Corn and soybeans are the major crops for the Midwest region, accounting for 38.3% and 31.3% of the planted acres, respectively, in the three surveyed states in 2019. All farmers plant both corn and soybean at the time of our survey. Corn and soybean are substitutes in production since they compete for the same agricultural land. The decision to produce corn and soybean is driven by profit maximization (profit=total revenue – total cost). Because of the biological lag between planting and harvest, farmers use projected prices to form expectations. The law of supply dictates that lower (expected) price leads to lower planting. In our case, farmers who are more pessimistic about soybean prices should decrease soybean acres.

Practically, the adjustment of the percentages of corn and soybean acres can be achieved through switching between two common crop rotation patterns: continuous corn and corn-soybean rotation (continuous soybean is also possible but may cause decreasing yield, Licht et al. 2021). The corn-soybean rotation saves fertilizer costs since soybean retains Nitrate, but it may deplete organic matter in the soil (Hall, Russell, and Moore 2019). If a farmer decides to decrease soybean planting, they can take acres out from the corn-soybean rotation and plant corn for another year. Historically, from 2000 to 2020, the ratio between corn and soybean acres in the three sample states fluctuated between 1.02 to 1.54, which attests to the adjustability of planting decisions.

2. Storage decisions

Grain storage after harvest is a common strategy adopted by farmers in the Midwest (Edward and Johanns, 2018). For example, the grain storage capacity in Iowa in 2018 was 1.45 billion bushels or 47.5% of the total corn and soybean production in that year. The primary reason for farmers to store grain is to capture price improvement after harvest (Dhuyvetter et al. 2007). In most years, the prices for corn and soybeans are at their lowest after harvest and gradually increase until close to the next harvest season. Other factors, including the trade war, will also affect the price trend, hence farmers' storage decisions.

When deciding how much grain to store, farmers weigh potential price gains against the cost of grain storage. Farmers can choose to store grain on-farm or in commercial grain elevators. Both options come with costs that increase with the quantity and duration of storage. For example, storage would postpone sales and delay loan repayment, creating interest costs. Other things equal, if farmers expect the future price to be lower than in a normal seasonal cycle, they would decrease storage since there is less price gain to justify the storage cost. Therefore, farmers who believe the trade war has a more negative impact use less grain storage. Grain storage facilities usually have redundant capacity (Janzen, 2020), which gives farmers the flexibility to change storage levels.

3. Pre-harvest marketing

As discussed in the storage section, when expecting lower prices in the future, farmers would reduce storage, thus selling more grains earlier at harvest. However, a farmer can sell their crop even earlier through pre-harvest marketing. Essentially, farmers can promise to deliver their still-growing crop at a pre-determined price to local grain merchants (Johnson 2018).

The cash price that farmers get when selling grains to a local merchant can be written as:

Cash price=futures price + basis

Where basis is defined as the difference between the futures price (determined by the national market) and the local price, which is determined by transportation costs, local storage availability, and so on, the two most commonly used tools for pre-harvest marketing are cash-forward contracts and hedge-to-arrive contracts (Johnson 2020). In cash-forward contracts, the farmers are directly offered a cash price to deliver the crop at a later time. In hedge-to-arrive contracts, only the futures price component is fixed, and the basis can still vary according to the market. If farmers expect downward price trends, they should use one of these tools. Which one to choose depends on the expectations about the basis, which has no obvious relationship with the trade war.

4. Spot vs. Non-spot market

The spot market is where commodities are traded, and payments are made at the time of the transaction. Therefore, the tools for pre-harvest marketing all fall under the umbrella of the non-spot market. In addition to pre-harvest marketing using cash-forward contracts and hedge-to-arrive contracts with local grain merchants, common non-spot market tools include futures and options. Farmers commonly use these tools to hedge against downward price risks (Prager et al. 2020, CME 2020). While these instruments can be used for purely speculative purposes, our survey instrument specifically asks for the usage of the non-spot market for grain marketing.

Simply put, a futures contract is the commitment to deliver goods at a specific time in the future (say December 2022) in exchange for payment (according to futures price) right now. To hedge against downward price risk, a farmer who has a crop in the field can sell futures now, get paid by the current futures price, and commit to delivering the crop later. When the time comes to deliver, it is possible for the farmer to deliver the crop physically. However, to reduce costs, most farmers would buy futures (releasing them from the duty to deliver). As they buy futures, they would also sell their crop on the cash market. The cost of buying futures and selling the actual crop after harvest will more or less cancel out (up to basis, see formula above). The farmer essentially sells the crop at a fixed earlier price using futures hedging.

Call and put options are derivative products of the futures market. They are the rights (but not obligations) to buy and sell futures at certain prices. Compared to hedging with futures, which lock in a certain price, hedging with options retains the upward potential when the price increases. A crop producer can buy put options, sell call options, or use a combination of the two to protect themselves from price decline (CME 2020). These strategies can be used before harvesting or in the storage stage. A farmer who assesses downward risk to be higher due to the trade war would use non-spot market marketing tools more.

References

Chicago Mercantile Exchange (CEM) Group. 2020. “Self-Study Guide to Hedging with Grain and Oilseed Futures and Options”

Prager, Daniel, Christopher Burns, Sarah Tulman, and James MacDonald. 2020. “Farm Use of Futures, Options, and Marketing Contracts.” USDA ERS Economic Information Bulletin 219

Dhuyvetter, Kevin C., Joseph P. Harner, III, Jenna Tajchman, Terry L. Kastens. 2007. “The Economics of On-Farm Storage.” Kansas State University Agricultural Experiment Station and Cooperative Extension Service, MF-2474

Edwards, William. 2018. “Grain Storage Alternatives: An Economic Comparison” Iowa State University Ag Decision Maker, A2-35

Hall, Steven J., and Ann E. Russell. 2019. “Do corn-soybean rotations enhance decomposition of soil organic matter?” Plant and Soil 444, no. 1: 427-442.

Janzen, Joe. 2020. “Changes in US Grain Storage Capacity.” *Farmdoc daily* (10):204

Johnson, Steve. 2018. “Risk Management Practices: Pre-Harvest Marketing New Crop.” Iowa State University Ag Decision Maker, A2-55

Johnson, Steve .2020. “Understanding Risk in Hedge-to-Arrive Contracts.” Iowa State University Ag Decision Maker, A2-74

Licht, Mark, Daren Mueller, Antonio Mallarino, Greg Tylka, Zachary Clements. 2021. “Considerations When Planting Soybean Back-to-back”, Iowa State University Extension and Outreach.

Appendix 4: Estimating farmers' actual loss from the trade war

To provide a benchmark for farmers' losses from the trade war, we follow Janzen and Hendricks's (2020) two methods of estimating actual losses from soybean and corn sales.[1] The first method uses price impacts according to the World Agricultural Supply and Demand Estimates (WASDE) 2018/19 season-average farm price forecast from May 2018. The forecasted soybean price for 2018–19 decreased by \$1.50/bushel, and the forecasted corn price declined by \$.20/bushel relative to the May 2018 WASDE season average price forecast, reflecting the impact of the trade war. Thus, we construct the first measurement of farmer i's actual income loss as:

$$RealLoss_{ic} = Soy_{ic} * SoyYield_c * 1.5 + Corn_{ic} * CornYield_c * 0.2, \tag{1}$$

where Soy_{ic} and $Corn_{ic}$ denote farmer $i's$ soybean and corn harvested area in 2018, respectively; and, $SoyYield_c$ and $CornYield_c$ denote the soybean and corn yield, respectively, in county c. Yield data is from the USDA National Agricultural Statistics Service (NASS 2020).

The second method uses the decrease in unit export value from before the trade war (2017/18) to after it started (2018/2019) to measure farmers' losses from the trade war. The unit price of US soybean exports to China declined by \$1.38/bushel, and that for corn declined by \$.01/bushel. We calculate the second measurement of real income loss as:

$$RealLoss_{ic} = Soy_{ic} * SoyYield_c * 1.38 + Corn_{ic} * CornYield_c * 0.01, \tag{2}$$

The notations in equation (3) are the same as in equation (2). To investigate whether media is associated with the gap between farmer's expected and actual income loss from the trade war, we construct the following measurement:

$$Gap_{ic} = Exp_{ic} - \frac{RealLoss_{ic}}{Income_{ic}} * 100\%, \tag{3}$$

where Exp_{ic} denotes farmers' self-reported percentage-of-income impact from the trade war; and, $\frac{RealLoss_{ic}}{Income_{ic}} * 100\%$ denotes the estimated actual percentage-of-income impacts from the trade war.

[1] Soybeans are the most affected agricultural commodity in the trade war. China imposed a 25% tariff on US soybeans on July 7, 2018, and an additional 5% tariff on September 1, 2019.

Table A5. Estimated actual income loss and the gap between actual and perceived income loss.

	Mean	SD	Min	Max
Actual income loss ($): Method 1	67,728	56,832	5,263	641,618
Actual share of income loss (share): Method 1	0.167	0.2	0.021	1
Actual income loss ($): Method 2	41,863	35,318	3,243	379,228
Actual share income loss (share) : Method 2	0.112	0.16	0.009	1
Gap between perceived and actual income loss shares: Method 1	0.3	0.48	0.022	4.059
Gap between perceived and actual income loss shares: Method 2	0.24	0.39	0.009	3.228
Market Facilitation Payments ($)	31,283	28,905	0	289,581
Share of Market Facilitation Payments in total farm income	0.12	0.18	0	1

Notes: This table reports the summary statistics for actual income loss estimated using method one (equation 1) and method two (equation (2)). The gaps between estimated and perceived income loss are calculated using equation (3).