Partisan bias in Statements Versus Behavior: Evidence from 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, Post-Doctoral Research Associate, Department of Economics and Center for Agricultural and Rural Development (CARD), Iowa State University, xihe@iastate.edu

Wendong Zhang*, Associate Professor, Department of Economics and Center for Agricultural and Rural Development (CARD), Iowa State University, wdzhang@iastate.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

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Abstract: Analyzing a 2019 Midwest farmer survey, we find that frequent use of conservative (liberal) media is associated with a 2.3% decrease (2.4% increase) in farmers' expected income loss from the US-China trade war and a 14.3% increase in the probability of perceiving Market Facilitation Program payments as helpful. Viewers of different media sources disagree on facts, including the level of China's retaliatory tariffs and the share of soybeans exported to China. However, we find little association between media exposure and farmers' economic decisions that mitigate the risk of a price decline. When substantial financial interest is at stake, partisan bias is present in statements about economic facts and perceptions, but not in economic decisions. The discrepancy shows that the partisan bias is not due to true belief but cheerleading behavior. Such cheerleading behavior disappears when reporting actual behavior.

Keywords: Political bias; Media; US-China trade war; Economic perceptions; Production and marketing behavior

JEL codes: D83; D84; Q13; Q18

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Introduction

Longstanding literature has documented how the "partisan screen" filters realities (Campbell et al. 1960, 133). In other words, people's perceptions of realities (Flynn, Nyhan, and Reifler 2017; Jerit and Barabas 2012; Jerit and Zhao, 2020; Taber and Lodge 2006), including economic conditions (Bartels 2002; Evans and Andersen 2006; Evans and Pickup 2010; Stanig 2013; Wlezien, Franklin, and Twiggs 1997), differ depending on whether the party they support presides over the economy. Some studies find the partisan bias can be reduced when economic facts are clear enough (Redlawsk, Civettini, and Emmerson 2010) and when rewards and admonitions are provided for accurate answers (Bullock et al. 2015; Peterson and Iyengar 2021; Prior, Sood, and Khana 2015). However, it remains unclear whether differences in reported perception reflect sincere beliefs (Bartels 2002; Jerit and Barabas 2012; Shapiro and Block-Elkon 2008) or partisan cheerleading (Hamlin and Jennings 2011; Schuessler 2000; Bullock and Lenz 2019). A limited number of studies (Gerber and Huber 2009; Gerber and Huber 2010; McGrath 2017) concerning people's behavior find that people do not always behave according to their reported perceptions (McGrath 2017), suggesting that people reach survey answers and behavioral decisions through different phycological processes.

Because existing studies primarily focus on the perceptions and behavior of the general public related to general economic conditions, it is unclear what happens when people's financial interest is directly affected. When substantial financial interest is at stake, it is likely people's information search and reasoning will be more rigorous and impartial. Would people's economic perceptions still be biased by their political views? Would individuals act upon their stated perceptions? These questions are important because people whose financial interests are directly affected by policies are more likely to take political actions than the general public. This study answers these questions by studying how Midwest farmers perceive the economic impacts of the ongoing US-China trade war and how their production and marketing decisions change as a result.

Since 2018, the US-China trade war has created waves of global trade tensions, triggered record tariff increases across sectors, and reversed several decades of globalization (Fajgelbaum et al. 2020; Li, Balistreri, and Zhang 2020). US farmers, a group with outsized political influence relative to their number (Anderson, Rausser, and Swinnen 2013), became a crucial force in the trade war. Both superpowers seek to influence US farmers through economic incentives, with China imposing several waves of retaliatory tariffs on US agricultural exports (Bown and Kolb 2021) and the United States subsidizing farmers with Market Facilitation Payments (MFP) (Balistreri, Zhang, and Beghin 2020; Glauber 2019). Although most US farmers support the Republican Party and the Trump administration (Wilson 2020), changing economic incentives puts political alignments to the test.

The US-China trade war offers a fortuitous scenario for our investigation. First, China's retaliatory tariffs and the United States' MFP created large and relatively predictable shocks on farmers' incomes. Therefore, one can consider the differences in perceived trade war impacts as the results of different political attitudes after controlling for crop production and other relevant farm characteristics. Second, farmers' perceptions of future price trends have clear behavioral implications (Choi and Helmberger 1993; Shonkwiler and Maddala 1985, also, see Appendix 1): if farmers expected soybean price to decline due to the trade war, they should reduce planting acres (i.e., the law of supply), sell the product early by decreasing storage and increasing pre-harvest sales (Kadjo et al. 2018), and use non-spot market tools (such as futures and options) to hedge against downward price risk (MacDonald 2020). These expected responses allow us to examine the consistency between stated perceptions and behavior.

In recent years, the media landscape in the United States has become increasingly polarized (Prior 2013), with audiences selecting media sources that conform with their views (Peterson and Iyengar 2021). As a result, people with similar political inclinations increasingly congregate around the same media sources. At the same time, liberal and conservative media cast the same events, including the trade war, in drastically different lights, potentially strengthening the partisan divide (Hoewe and Peacock 2020; Jamieson and Cappella 2008). This study focuses on how farmers' economic perceptions and behavior differ by consuming liberal or conservative media. Given the increasingly close connection between political alignment and media consumption, we interpret the effects of media exposure as evidence for how political alignment affects perceptions and behavior. This interpretation is bolstered by the fact that most farmers either use liberal or conservative media exclusively as their most frequent sources in our data.

We collected our data from a 2019 survey of 472 crop farmers in the Midwestern states of Iowa, Illinois, and Minnesota. These three states are the top three soybean-producing states in the country, accounting for 16.4% of US agricultural cash receipts and 11.1% of US corn and soybean exports in 2019 (NASS 2020). To examine how farmers' perceptions of and responses to the trade war differ by media exposure, we first classify all self-reported media outlets into three categories—conservative (e.g., Fox News), liberal (e.g., MSNBC), and neutral (e.g., *Successful Farming* magazine)—based on the ideological placement of an information outlet's audience by the Pew Research Center (Mitchell et al. 2014) and the expert opinions of extension farm management specialists. We examine the role of exposure to these media channels with varying ideological leanings in three sets of outcomes: (*a*) expected loss of income from the trade war and perceptions of the helpfulness of the MFP; (*b*) knowledge about China's tariff rate on US soybeans, the share of soybeans exported to China, and MFP payment rate for soybean producers; and, (*c*) economic decisions about soybean storage, planting, and marketing.

We report three findings. First, political bias does affect economic perceptions. Frequent exposure to conservative media is associated with a 2.3% decrease in farmers' expected income loss, and frequent exposure to liberal media is weakly ($p<10\%$) associated with a 2.4% increase in farmers' expected income loss. The implied gap in expected income loss is 4.7% between farmers who only list liberal and those who only list conservative media in their top three sources. Given that farmers on average estimate a 14.4% expected income loss, the equivalent of \$94,445 per year, the gap of 4.7% equals \$30,810 per year. USDA estimates show that the heartland region's average net farm cash income is \$110,800 in 2018. Therefore, the estimated income loss gap of \$30,810 is economically large in magnitude.[1] Also, frequent exposure to conservative media is associated with a 14.3% increase in the probability of farmers perceiving MFP payments as helpful, and exposure to liberal media is associated with a 7.4% (statistically insignificant) decrease in the probability of farmers perceiving MFP payments as helpful. In other words, exclusive conservative media consumers are 21.7% more likely to find MFP payments helpful than exclusive liberal media consumers.

Second, the differences in economic perceptions extend to disagreements on basic facts. When asked about China's tariff rate on US soybeans (25%) and the percent of US soybean

1 We only sampled farms with more than 250 acres of land in operation, which accounted for around 66% of farms and 90% of harvested cropland in the three sampled states.

exports exported to China (60%), farmers who are frequently exposed to conservative media give answers that are on average 1.4% and 2.5% lower than others ($p<0.1$), and are 8.4% less likely to overestimate either the tariff rate or export share ($p<0.05$). In other words, the consumers of conservative media believe in facts that diminish the impacts of the trade war.

Third, there is little association between media exposure and farming and marketing behavior. For soybeans, the most affected commodity, neither liberal nor conservative media has any statistically significant impact on surveyed farmers' storage, planting, pre-harvest versus post-harvest marketing decisions, and their utilization of spot versus non-spot markets. Though imprecise estimation may cause the lack of behavioral responses in individual outcomes, the null results in all outcomes are evidence that behavioral responses are at least small, if not non-existent.

This article relates and contributes to two significant lines of literature. First, we add to the previous literature on partisan bias in economic perceptions (Bartels 2002; Evans and Andersen 2006; Evans and Pickup 2010; Stanig 2013; Wlezien, Franklin, and Twiggs 1997) by showing that the partisan screen exists even when a policy directly affects individuals' economic conditions. The partisan differences in economic perceptions partially stem from disagreements in basic facts. Second, our article contributes to the literature on political bias and perception-behavior (in)consistency (Gerber and Huber 2009; Gerber and Huber 2010; McGrath 2017). We find no statistically significant evidence that political bias extends to actual behavior, suggesting that cheerleading does not extend to actual behaviors.

Theory and Hypotheses

The literature has attributed partisan bias to three sources. First, people with different political affiliations selectively consume and absorb (Jerit and Barabas 2012, Kim and Kim 2021, Mitchell et al. 2014) information, especially under a polarized media environment. The difference in information may be in its content: for example, a Fox News report may say the trade war is beneficial to the US, while an MSNBC report may claim it detrimental. The difference in information can also be in the frequency of exposure: a person who mostly watches Fox News may hear positive arguments about the trade war more frequently, while the reverse may be true for an MSNBC viewer.

Second, people may process the same information differently based on their motives. The theory of motivated reasoning (Kunda 1990; Bullock and Lenz 2019) suggests that reasoning may be driven by "accuracy goal" or "directional goal." Reasoning with the accuracy goal seeks to find objectively accurate answers. In contrast, reasoning with a directional goal tries to reach conclusions in a particular direction to "protect one's existing beliefs or identities. (Bolsen and Palm 2019)." Directional goals can be achieved by selectively accessing beliefs, selectively evaluating research, and selectively using inferential rules (Kunda 1990). As such, directional goals are constrained by available information and reasoning processes.

Third, people may engage in "cheerleading," which means they provide answers favorable to their political party but not based on any reasoning process (Bullock et al. 2015; Peterson and Iyengar 2021). When cheerleading, survey respondents do not believe in their answers, unlike motivated reasoning with directional goals. If the purpose of a survey is to gauge people's true opinions, the cheerleading jeopardized the validity of the survey instrument.

This study considers two sets of survey statements: 1) perceptions about the trade war, including the impacts of tariffs on income and the helpfulness of the MFP program; 2) knowledge on basic facts, namely the share of soybean exported to China, the level of retaliatory tariffs on soybeans applied by China, and the level of MFP payments. If there is partisan bias in information, directionally motivated reasoning, or cheerleading, we hypothesize that consumers of conservative (liberal) media to report lower (higher) negative impacts from tariffs (**H1a**), more (less) helpfulness of MFP (**H1b**), lower (higher) soybean export share to China (**H1c**), lower (higher) tariff rates on soybeans (**H1d**), and higher MFP payment rates (**H1e**). The corresponding null hypotheses (H0a~H0e) are for conservative and liberal media consumers to have the same perceptions on these issues relative to non-consumers.

If farmers expect soybean price to decline due to the U.S. China trade war, they should take measures to mitigate the risk of the price decline. These measures range from the straightforward reaction of decreasing soybean acres to the more sophisticated methods of hedging using futures and options (see Appendix for an introduction to these measures). First, if farmers believe that the trade war has a larger negative impact on the profitability of soybean production (combining tariff and MFP impacts), they should decrease soybean planting according to the law of supply (**H1f**, Choi and Helmberger 1993). Second, if farmers are pessimistic about the price of soybeans price, they should sell the products early by reducing storage (**H1g**) and increasing pre-harvest sales (**H1h**) as opposed to post-harvest sales (Kadjo et al. 2018). Finally, if farmers expect the trade war to create downward price risks, they should reduce the risk through pre-harvest sales and other the non-spot market tools (including futures and option) (**H1i**, MacDonald 2020). The null hypotheses (H0f~H0i) are for conservative and liberal media consumers to exhibit the same behavior in the above aspects relative to non-consumers.

Rejections of any null hypotheses (H0a~H0i) would indicate that at least one of the three sources of partisan bias is at work, but it is not clear which one. Failures to reject would indicate a lack of support for partisan bias from all sources. Inconsistencies in partisan bias in perceptions, knowledge, and economic decisions are evidence for partisan cheerleading and against motivated reasoning.

A limitation of this study is the reliance on media consumption to classify political alignments. However, we believe this limitation is inconsequential to our key results. First, because of the highly polarized media landscape in the United States, media consumption is a good proxy for political alignment. We find empirical support for that in our data. Second, on average, people aligned with republican and democratic parties also have different media exposures (Mitchell et al. 2014). Therefore, even if we have explicit measures of political alignments, the observed partisan bias would not be free from media effects. For these reasons, we do not expect to get qualitatively different results if we use direct measures of political attitudes.

Data and Summary Statistics

Survey

From March to June 2019, we sent both mail and online surveys to 3,000 crop farmers over the age of 18 with at least 250 acres of cropland in Iowa, Illinois, and Minnesota.[2] We selected

2 The average farm size in the US is 444 acres in 2020. Our sample selection of farms with at least 250 acres might limit the generalizability of the results to medium to large farms and we should be cautious extending our findings to small farms. We choose this sampling criteria to

respondents through stratified sampling. Forty-four percent of our sample came from Iowa, 32% from Illinois, and 23% from Minnesota. The survey asked about farmers' demographic and farm characteristics, most frequently used media sources, expected farm income loss from the trade war, perceived helpfulness of the first round of MFP payments in 2018, and various farming and marketing decisions. We received 722 responses (a 25.8% response rate). After dropping respondents who did not provide expected income loss from the trade war (a main outcome of interest) and other important farm characteristics, 472 usable observations remained.[3] Figure 1 shows the county locations of surveyed farmers' primary farm operations and county-level soybean planted acres in 2018.[4]

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exclude recreational and part-time farmers for whom economic considerations may be less important.

[3] We test whether there is a selection problem due to missing observations and find no correlation between the probability of a missing answer and farmers' education and age and farming attributes such as soybean and corn planted acreage.

[4] Large farming operations may own multiple farms, which may encompass multiple counties or states (MacDonald 2020). Our survey asked for the location of the primary farm. Six respondents reported that their primary farms are outside the three states.

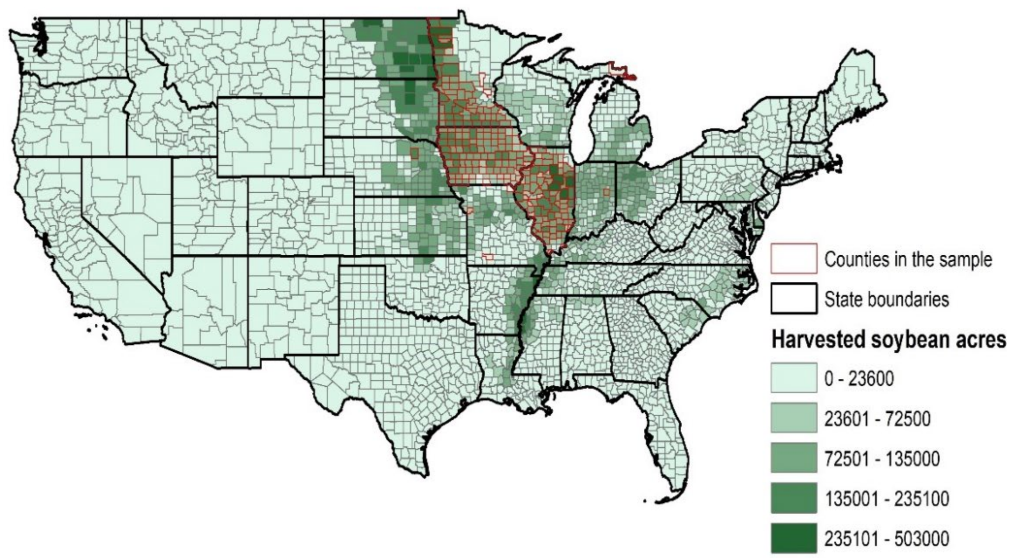

Figure 1. Counties in sample and soybean planted acres.

Notes: This figure shows the counties where the farmer-respondents reside and the county-level soybean planted acres across the contiguous United States in 2018. There are 472 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.

Key Variables

Table 1 presents selected survey questions from which we derive our main variables. The key independent variable, media exposure, comes from the open-ended question, "When seeking information about the trade disruption, what are your three most frequently used media sources?" The survey allows respondents to answer less than three sources. We classify the reported media outlets into three categories—conservative, liberal, and neutral. We first classify conservative and liberal media sources based on the ideological placement of each media outlet's audience from a study by the Pew Research Center (Mitchell et al. 2014). For local and farm-related media sources not covered by the Pew Research Center study, we determine the liberal or conservative classification based on the expert opinions of farm management specialists from Iowa State University Extension. We categorize media sources not covered by the Pew Research Center study and not recognized by experts as partisan as "neutral" media sources.[5] We conduct robustness checks using Fox News as conservative outlets and reached similar conclusions. Table A1 in the Appendix shows farmers' most frequently used conservative news source is Farm Bureau publications (32.6% of all farmers), closely followed by Fox News (28.6%). CNN is the most frequently used liberal source (10.8%), and *Successful Farming* magazine is the most frequently used neutral source (31.6%).

Table 1. Selected Survey Questions for Dependent Variables

Variables	Question	Answer choices
Media exposure		
Media exposure	When seeking information about the trade disruption, what are your three most frequently used media sources?	Open-ended
Beliefs		
Expected 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?	Categorical variable from 1 (Up more than 20%) to 9 (Down more than 20%)
Belief that the Trump administration's $12 billion trade relief plan will be beneficial to your farm	How helpful do you think President Trump's $12 billion trade relief plan will be to your farm?	Categorical variable from 1 (Not at all helpful) to 5 (Very helpful)
Knowledge of the US soybean market		

[5] We exclude Facebook and Twitter from the analysis, given that it is hard to classify them into the three media types.

	To the best of your knowledge, what percent of tariff did the Chinese government impose on US soybean exports in July 2018?	a.10%, b.15%, c.25%, d.35%, e.45%
	To the best of your knowledge, what percentage of US soybean exports were shipped to China in 2017?	a.10%, b.30%, c.45%, d.60%, e.75%
	President Trump announced a Market Facilitation Program to help farmers affected by the trade disruptions in 2018. To the best of your knowledge, what was the payment rate for soybean producers?	a. 1 cent per bushel, b. 14 cents per bushel, c. 86 cents per bushel, d. $1 per bushel, e. $1.65 per bushel
Behavior		
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?	Categorical variable from 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 [marketing] 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 using marketing tools] for 2019?	Continuous variable from 0–1

Notes: The questionnaire contains 39 questions in total. This table lists the questions and answer choices for the measurement of media exposure and farmers' beliefs, behavior, and knowledge of the US soybean market.

The first set of outcomes we examine is farmers' expected income loss and perceived benefits from the MFP payments. The expected income loss from the 2018 trade war is a categorical variable scaling from 1 (Down more than 20%) to 9 (Up more than 20%). To gauge the accuracy of farmers' expected income loss, we also estimate actual income loss using two alternative specifications proposed by Janzen and Hendricks (2020) and calculate the gap between estimated loss and self-reported expected loss. We measure the benefit of MFP payments on a five-point scale, from "Not helpful at all" to "Very helpful." The second set of outcomes includes farmers' knowledge of Chinese tariffs on US soybeans, China's share in US soybean exports, and the level of MFP payments for soybeans. The knowledge questions have choices that range from too low to too high. The third set of outcomes involves farmers' decisions regarding soybean storage, planting, and marketing. Marketing includes the timing of sales (pre-, at-, and post-harvest) and the use of spot vs. non-spot marketing tools (e.g., futures, options, and other grain contracts).[6] We measure whether farmers increase their soybean storage on a five-point scale, from "Decrease a lot" to "Increase a lot." We measure farmers' soybean planting behavior using their share of soybeans in total planted acreages. Marketing behavior include the shares of soybeans marketed in spot and non-spot markets, and pre-, at-, or post-harvest.

Summary Statistics

Table 2 presents summary statistics of the main variables used in our analysis. Farmers sought information about the US-China trade war mainly from neutral media (55.5%), followed by conservative (53.0%) and liberal (24.2%) media.[7] Among the 472 participants, only 49 (10.4%)

[6] The spot market is a market in which commodities are traded for immediate delivery. Non-spot marketing tools include futures, options, and other grain contracts. Commodities traded on non-spot markets are often delivered at a later date.

[7] Farmers' use of media with a particular ideological leaning may not be exclusive. They can get information from conservative, liberal, and neutral media or any combination of the three.

use liberal and conservative media simultaneously, and 66.7% use liberal or conservative media exclusively as their most frequent sources. The segregation of conservative and liberal audiences supports our interpretation of media exposure as a proxy for political bias. The survey asks for average expected income loss as a categorical variable, from 1 (Up more than 20%) to 9 (Down more than 20%). When we convert the scale variable to the mean of the upper and lower bounds that define each category,[8] the average expected income loss is 14.4%.

Table 2. Summary Statistics

	Mean	SD	Min	Max
Media exposure				
Conservative	0.530	0.500	0	1
Liberal	0.242	0.428	0	1
Neutral	0.555	0.497	0	1
Economic Perceptions				
Expected income loss (9=Down more than 20%; 5=No change; 1=Up more than 20%)	7.686	1.521	1	9
Expected income loss (%)	14.407	9.661	-25	25
Belief on whether Market Facilitation Payments are helpful (1=Not at all helpful; 5=Very helpful)	3.609	1.104	1	5
Knowledge of Trade War-Related Facts				
Knowledge of percent of tariff the Chinese government imposed on US soybean exports in July 2018 (Correct answer: 25%)	24.375	7.71	10	45
Knowledge of percent of US soybean exports shipped to China in 2017 (Correct answer: 60%)	47.143	15.611	15	75

[8] 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%. These conversions are not accurate reflections of farmers' expected income loss and would likely bias our estimates of the impacts of media.

Knowledge of the level of the MFP payment rate for soybeans in 2018 (Correct answer: 165 cents per bushel) (Unit: Cent)	157.6	27.5	1	165
Behavior				
Storage				
The impact of trade disruption on soybean storage change (1=Decrease a lot; 3=No change; 5=Increase a lot)	3.387	0.93	1	5
Planting				
Share of soybeans planted in 2018	0.470	0.128	0.100	1
Share of corn planted in 2018	0.543	0.132	0.100	1
Marketing				
Share of soybeans marketed in spot market in 2018	0.538	0.208	0	1
Share of soybeans marketed in non-spot market in 2018	0.462	0.208	0	1
Share of soybeans market pre- or at-harvest in 2018	0.464	0.289	0	1
Share of soybeans market post-harvest in 2018	0.536	0.289	0	1
Actual income loss, MFP payments, Gap between expected and actual net income loss				
Actual income loss from trade war ($): Method 1	67,934	56,900	5,263	643,465
Actual share of income loss from trade war: Method 1	0.167	0.201	0.021	1
Actual income loss from trade war ($): Method 2	42,022	35,387	3,243	380,320
Actual share income loss from trade war: Method 2	0.112	0.165	0.009	1
Gap between expected and net income loss: Method 1	0.32	0.493	0.035	4.07
Gap between expected and net income loss: Method 2	0.253	0.4	0.02	3.237
Market Facilitation Payments ($)	50,013	42,132	3,859	452,350
Share of Market Facilitation Payments in total farm income	0.13	0.179	0.011	1
Control variables				
Soybean planted acreage in 2018 (Acres)	497.248	411.303	43.571	4261.642
Soybean production in 2018 (Bushel)	29,598	24,984	2,283	266,779
Corn planted acreage in 2018 (Acres)	594.163	558.998	49.944	6392.463
Corn production in 2018 (Bushel)	117,688	109,419	9,190	1,216,486
Share of land rented	0.603	0.28	0	1
Non-irrigation cash rent ($)	210.368	42.8	42	289

Age	60.581	10.547	27	85
Attend some college or above	0.356	0.479	0	1
Male	0.97	0.17	0	1
Willingness to take risks (1=Not at all willing; 7=Very willing)	4.472	1.273	1	7
Have livestock on farm	0.379	0.486	0	1
Have off-farm job	0.686	0.464	0	1
Farm income ($)	655,551	482,542	30,000	1,500,000

Notes: Though we received 722 valid responses, we drop observations with missing answers to the main question on farmers' expected income loss from trade disruptions and additional control variables, resulting in 472 observations in the analysis.

To compare farmers' expected income loss with actual income loss, we follow Janzen and Hendricks (2020) and estimate farmers' income loss using two methods. Depending on the calculation method used, the estimated average actual loss is 11.2% or 16.7%. The average perception of whether MFP is helpful is 3.6 on a scale from 1 (Not at all helpful) to 5 (Very helpful), with 39.6% of farmers saying it is somewhat helpful, 21.2% of farmers saying it is quite helpful, and 27.8% of farmers saying it is very helpful. In the remaining analysis, we aggregate these three categories as helpful and the remaining two categories (Not at all helpful and Not sure) as not helpful.

We also study farmers' beliefs about basic underlying facts that may affect their perception of trade war impacts. Regarding China's retaliatory tariff rate on US soybeans, 64.2% of farmers answered the question correctly, and 21.3% and 14.5% chose numbers that are too low and too high, respectively. Regarding what percentage of US soybean exports go to China, 34.3% of farmers answer the question correctly, and 58.0% and 7.7% of farmers underestimated and overestimated, respectively. On the MFP payment rate for soybean producers, 92.3% of farmers answered the question correctly ($1.65/bushel), and 7.7% of farmers underestimated it.

In 2018, respondents planted an average of 497 acres of soybeans and 594 acres of corn. On average, the amount of soybeans respondents stored increased in 2018. Farmers sold averages of 46.4% of their soybeans pre- and at-harvest and 53.6% post-harvest. Furthermore, respondents sold 53.8% of soybeans in the spot market and 46.2% in the non-spot market, including futures, options, and other grain contracts.

Empirical Methods

Econometric Model

The econometric model we use to test the role of exposure to conservative, liberal, and neutral media in economic perceptions and farming behavior is:

$$Y_{ics} = \alpha_0 + \beta_0 Cons_{ics} + \beta_1 Lib_{ics} + \beta_2 Neu_{ics} + \gamma Z_{ics} + FE_s + \varepsilon_{ics}, \tag{1}$$

where Y_{ics} denotes the outcome of interest; $i, c,$ and s are the indexes for individuals, counties, and states, respectively; and, $Cons_{ics}, Lib_{ics}$, and Neu_{ics} represent farmer $i's$ exposure to conservative, liberal, and neutral media, respectively. In the main analysis, we use dummies to measure media exposure. Specifically, $Cons_{ics}$ $(Lib_{ics}, and\ Neu_{ics})$, equals one if a farmer listed at least one conservative (liberal, neutral) media outlet as a frequent information source, zero otherwise. Exposure to conservative, liberal, and neutral media is not mutually exclusive. We also check the robustness of the results using the share of different media types as an alternative measurement of media use.

To alleviate the concern of omitted-variable bias, we include a rich set of control variables, Z_{ics}, that include farmer demographic characteristics and farm characteristics. 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. We include state fixed effects, FE_s, to capture time-invariant differences across states. We cluster the error term (ε_{ics}) 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 Ordinary Least Square (OLS) regression or continuous variables, interval regression (Billard and Diday 2000) for categorical variables with known cutoff points, and the probit and ordered probit models and for ordinal variables. Average marginal effects are reported for probit and ordered probit models.

Farmers' Actual Income Losses

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.[9] 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:

[9] 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.

$$RealLoss_{ic} = Soy_{ic} * SoyYield_c * 1.5 + Corn_{ic} * CornYield_c * 0.2, \quad (2)$$

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:

$$RealLoss_{ic} = Soy_{ic} * SoyYield_c * 1.38 + Corn_{ic} * CornYield_c * 0.01, \quad (3)$$

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:

$$Gap_{ic} = Exp_{ic} - \frac{RealLoss_{ic}}{Income_{ic}} * 100\%, \quad (4)$$

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

USDA provided two rounds of MFP payments to farmers in 2018 and 2019. Our survey questions referred only to the first round (2018).[10] The 2018 MFP payment rates were \$0.01/bushel for corn and \$1.65/bushel for soybeans. As the estimated actual losses according to the second method are higher than farmers' expected income loss, it is possible that farmers overlooked survey instructions to the contrary and included the MFP payments into their reported expected income loss. Therefore, we also calculate farmers' MFP payments in 2018 using their corn and soybean production and the corresponding payment rate. We present results excluding and including MFP payments when analyzing the gap between expected and actual income loss.

Results

Perceived Economic Conditions

To visualize the relationship between soybean production and farmers' perceived economic conditions, we present the LOWESS (Cleveland 1981)[11] plot of and expected income loss in Figure 2.1 and the LOWESS plot of soybean production and the probability that farmers perceive MFP payments as helpful in Figure 2.2. Figure 2.1 shows that for most levels of soybean production, farmers who consume liberal media have a higher expected income loss

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[10] USDA distributed 2018 MFP payments during the period of data collection. USDA had not finalized MFP payments for 2019 at the time of the survey and thus we did not ask respondents about them.

[11] Lowess performs locally weighted scatterplot smoothing (Cleveland 1981).

than farmers who are conservative media consumers. Figure 2.2 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.

Table 3 presents the estimated results on how exposure to media of different political orientations is associated with farmers' expected income loss and whether they think the MFP payments are helpful. Column (1) presents the interval regression results when the expected income loss is measured using interval variables. Columns (2) and (3) show the media's association with the gap between farmers' expected and actual income losses as measured by two alternative methods. Columns (4) and (5) show the media's association with the gap between farmers' expected and actual income loss using two different methods when we include MFP payments in farmers' actual income loss. Column (6) shows the media's role in farmers' beliefs about whether MFP payments are helpful.

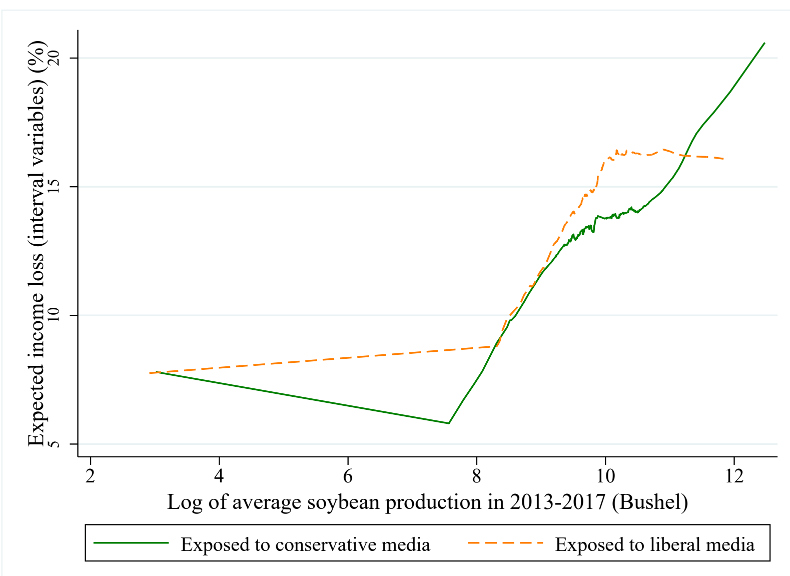

Figure 2.1 Average soybean production in 2013-2017 and expected income loss.

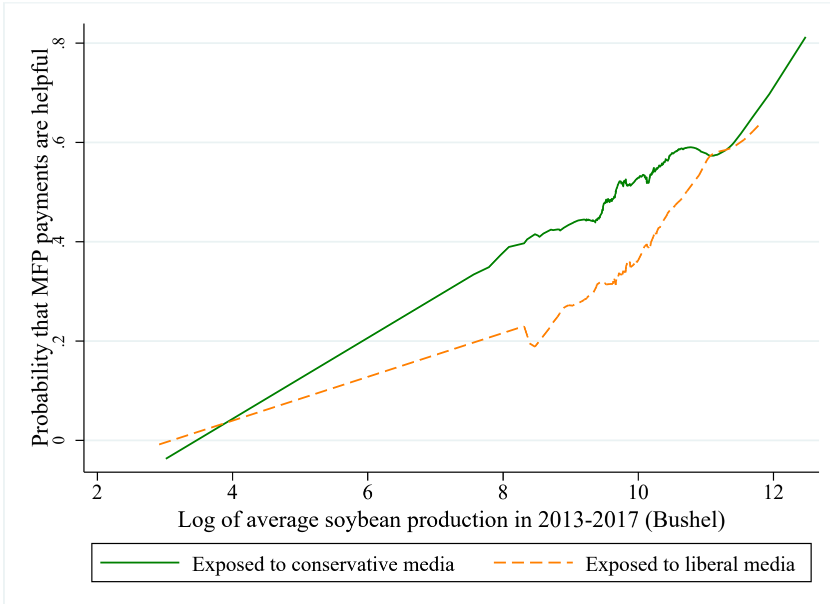

Figure 2.2 Average soybean production in 2013-2017 and the probability of perceiving MFP payments as helpful.

Table 3. Media Exposure and Farmers' Expected Income Loss, the Gaps between Expected and Actual Income Loss, and Beliefs about MFP Payment Helpfulness

	Interval regression	OLS		OLS		Probit
	Expected income loss (interval variables)	Gap between expected and actual income loss (method 1)	Gap between expected and actual income loss (method 2)	Gap between expected and actual income loss (method 1 with MFP payments)	Gap between expected and actual income loss (method 2 with MFP payments)	MFP payments are helpful (Dummy)
	(1)	(2)	(3)	(4)	(5)	(6)
Log of soybean production in 2018	2.586**	-8.697***	-8.915***	3.645***	3.428***	0.152***
	(1.245)	(1.677)	(1.789)	(0.997)	(0.926)	(0.052)
Log of corn production in 2018	-1.264	-11.408***	-5.692***	-6.165***	-0.449	-0.110**
	(1.292)	(1.515)	(1.628)	(1.239)	(1.146)	(0.054)
Exposure to conservative media	-2.289**	-2.154*	-2.595**	-1.339	-1.780*	0.143***
	(1.095)	(1.271)	(1.308)	(0.962)	(0.945)	(0.046)
Exposure to liberal media	2.438*	2.046	1.670	2.223*	1.847	-0.074
	(1.277)	(1.501)	(1.606)	(1.188)	(1.153)	(0.053)
Exposure to farm-related media	1.490	1.546	1.811	0.942	1.206	-0.043
	(1.092)	(1.281)	(1.315)	(0.938)	(0.925)	(0.046)
Age	-0.089*	-0.010	-0.039	-0.055	-0.083	-0.007***
	(0.054)	(0.068)	(0.069)	(0.055)	(0.051)	(0.002)
Have some college (Dummy)	-0.354	-1.164	-1.577	0.100	-0.313	-0.074*

	(1.134)	(1.381)	(1.400)	(1.006)	(0.951)	(0.048)
Male	-2.510	-1.514	-1.398	-2.220	-2.105	0.226
	(3.146)	(3.321)	(3.264)	(2.350)	(2.421)	(0.13)
Risk preference (Scale from 1 to 7)	-0.495	-1.026**	-1.045**	-0.440	-0.459	0.02
	(0.429)	(0.475)	(0.489)	(0.358)	(0.368)	(0.018)
Log of farm income	-0.421	23.136***	17.537***	3.367***	-2.231***	-0.007
	(0.694)	(1.229)	(1.386)	(0.848)	(0.657)	(0.029)
Have livestock	-1.334	-2.882*	-2.872*	-1.077	-1.067	0.025
	(1.094)	(1.475)	(1.486)	(1.080)	(1.050)	(0.047)
Have off-farm income (Dummy)	0.424	0.105	0.019	0.395	0.310	0.077
	(1.159)	(1.352)	(1.339)	(1.030)	(0.909)	(0.05)
Log of farmland cash rents (County non-irrigated land cash rent*Share of land	-0.006	-0.009	-0.011	-0.003	-0.005	-0.0003
	(0.009)	(0.010)	(0.010)	(0.008)	(0.007)	(0.0004)
Observations	472	472	472	472	472	470

Notes: This table presents the estimation results of the effect of media exposure on farmers' expected income loss and whether they think the MFP payments are helpful. Column (1) presents the interval regression results when we measure the expected income loss as interval variables. Columns (2) and (3) present the OLS results for the gap between expected and actual income loss as measured by equations (2) and (3). Columns (4) and (5) present the OLS results for the gap between expected and actual income loss when we include MFP payments in farmers' actual income loss to account for the possibility that farmers might unconsciously account for the

MFP payments when reporting their expected income loss. Column (6) shows the marginal effects from probit estimation results of media exposure on farmers' beliefs as to whether MFP payments are helpful. We include state fixed effects in all specifications and cluster standard errors at the state level when using OLS. Standard errors are in parentheses. *, **, and *** denote significance level at the 0.1, 0.05, and 0.1 level, respectively.

We observe the following results. There is strong evidence that conservative media exposure relates to significantly lower expected income loss, while liberal media exposure has a positive association ($p<10\%$) with expected income loss. In column (1), interval regression results show that farmers frequently exposed to conservative media report a 2.3% lower expected income loss. Given that survey participants reported an average gross income of $655,551 in 2018, the 2.3% decrease in expected income loss would mean a decrease of $15,005, which is economically significant.[12] Columns (2) and (3) show that when we measure the actual loss using the two methods proposed by Janzen and Hendricks (2020), we find a negative association between conservative media exposure and the gap between expected and actual income loss (ranging from 2.2% to 2.6%, with significance level ranging from 5% to 10%). For liberal media exposure, column (1) shows that farmers who are frequently exposed to liberal media report a higher expected income loss (2.4%) at the significance level of 10%. In our sample, 66.7% of farmers list either liberal or conservative media as their most frequently used sources (with or without neutral sources). The implied gap in expected income loss between liberal-only and conservative-only audiences (with and without consuming neutral media) is 4.7%, or $30,811. These findings suggest that farmers frequently exposed to conservative and liberal media substantially differ in their expected income loss. Consumers of conservative media are more

[12] USDA estimates shows that an average farm business's net cash income in the heartland region is $110,800 in 2018. The estimated income decrease of $15,005 accounted for around 13.5% of an average farm's net cash income. Note that we only sampled farms with more than 250 acres of land in operation that accounted for around 66.8% of farms in the three sampled states.

optimistic about the trade war's impacts on their income, while consumers of liberal media are more pessimistic.

Results in column (6) indicate that frequent conservative media use increases the probability of farmers considering MFP payments helpful by 14.3%. In comparison, exposure to liberal media decreases the possibility of viewing MFP payments as helpful by 7.4%, although the coefficient is not statistically significant. The gap in whether farmers find MFP payments helpful is 21.7% between farmers who only consume conservative media and those who only consume liberal media (with and without consuming neutral media). In terms of the control variables, older farmers are less likely to think that MFP payments are helpful. As a robustness check, we provide another set of results using ordered probit models. Table A2 in the Appendix presents the estimated marginal impacts. The main findings remain robust.

Notably, as table 3 column (1) shows, farmers who produce more soybeans expect more income loss and, as column (6) shows, are more likely to believe that MFP payments are helpful. These results are expected considering that both China's retaliatory tariffs and the United States' MFP payments target soybeans. Despite the political bias, economic reality still shapes perceptions to some extent.

Overall, the results in table 3 show that conservative media exposure is associated with lower expected income loss and a higher probability of finding MFP payments. Liberal media exposure, on the other hand, is associated with higher expected income loss and a lower probability of finding MFP payments are helpful. These findings support hypotheses H1a and H1b. Given that farmers' media use reflects their political inclination and bias, these findings indicate that political bias is associated with farmers' economic perceptions of their income loss from the trade war and whether MFP payments are helpful. These findings add to previous studies on the impact of political bias on people's economic perceptions by showing that the partisan screen is also at work when a policy directly affects individuals' economic conditions.

Knowledge of Trade War-Related Facts

To understand why media exposure is associated with biased expected income loss, we check if media exposure is associated with farmers' knowledge of China's retaliatory soybean tariffs (25%), the share of US soybean exports shipped to China in 2017 (60%), and the MFP payment rate for soybean producers ($1.65/bushel). We use OLS regression and regress farmers' answers in percentage on media exposure and control variables. As table 4 column (1) shows, we find that frequent exposure to conservative media is associated with a 1.4% lower tariff rate estimate and, as column (2) shows, a 2.5% lower export share estimate. Both associations have p-values that are below 10% but above 5%. Because both facts affect the economic impacts of the trade war, we analyze whether farmers overestimate or underestimate either of these two facts. Marginal effects from probit regressions show that the probability of overestimating either tariff or US export to China is 8.4% ($p<0.05$) lower for farmers who consume conservative media (table 4 column (3)). These findings support hypotheses H1c and H1d. The effect of conservative media on underestimation of these facts (+) and the effects of liberal media on overestimation (+) and underestimation (-) are also in the expected direction but are not statistically significant (table 4 column (3) and (4)). Table 4 column (5) shows that exposure to conservative media is associated with a statistically insignificant 3% higher MFP soybean payment rate. Therefore, we fail to reject the null hypothesis H0e. The lack of statistical significance in MFP results is not surprising as the US government had just announced the MFP at the time of the survey, and thus the vast majority of farmers knew the correct answer. As tariff rate and export share to China positively relate to the severity of trade war impacts, these findings indicate that farmers exposed to conservative media perceive facts in a way that diminishes trade war impacts. This is a potential explanation for why media exposure is associated with biased expected income loss.

Table 4. Media Exposure and Farmers' Knowledge

	Tariffs China imposed on US soybeans	Share of US soybean exports shipped to China	Answer too high for tariff or export question	Answer too low for tariff or export question	MFP payment rate for soybean producers
	(1)	(2)	(3)	(4)	(5)
Log of soybean production in 2018	1.072	1.874	0.027	-0.012	7.387
	(0.897)	(1.714)	(0.043)	(0.053)	(4.563)
Log of corn production in 2018	-0.443	-3.188*	-0.009	0.021	-7.288*
	(0.873)	(1.758)	(0.043)	(0.054)	(3.888)
Exposure to conservative media	-1.371*	-2.548*	-0.084**	0.065	3.006
	(0.793)	(1.440)	(0.037)	(0.046)	(2.657)
Exposure to liberal media	0.733	-0.165	0.036	-0.021	-0.640
	(0.779)	(1.915)	(0.043)	(0.054)	(3.400)
Exposure to farm-related media	0.961	2.733*	0.06	-0.095**	1.245
	(0.639)	(1.483)	(0.037)	(0.046)	(2.646)
Age	-0.024	-0.114	0.0004	0.005	-0.293*
	(0.030)	(0.078)	(0.002)	(0.002)	(0.158)
Have some college (Dummy)	-1.986***	0.692	-0.082**	0.002	-2.871
	(0.748)	(1.651)	(0.040)	(0.048)	(3.155)
Male	-0.350	-5.285	-0.071	0.309**	10.549
	(2.574)	(5.450)	(0.096)	(0.133)	(11.244)
Risk preference (from 1 to 7)	0.115	0.749	0.002	-0.015	-0.663
	(0.330)	(0.669)	(0.015)	(0.019)	(1.013)
Log of farm income	-0.569	1.006	-0.053**	-0.024	2.272
	(0.511)	(1.015)	(0.021)	(0.029)	(1.999)
Have livestock (Dummy)	-0.053	-0.921	0.07*	0.059	-1.654
	(0.833)	(1.570)	(0.036)	(0.047)	(2.756)
Have off-farm income (Dummy)	1.887**	-0.650	0.07*	-0.021	2.388
	(0.852)	(1.766)	(0.041)	(0.049)	(3.199)
Log of farmland cash rents	-0.007	0.010	-0.0002	0.0001	0.008
	(0.006)	(0.012)	(0.000)	(0.000)	(0.022)
Observations	456	455	470	470	469

Notes: Columns (1)–(5) present OLS estimations of the role of media exposure in farmers' knowledge of China's tariffs on US soybeans, the share of US soybean exports shipped to China in 2017, and the first round of MFP payments for soybean producers. For knowledge of China's tariffs, answers include 10%, 15%, 25%, 35%, 45%. For knowledge of the share of US soybean exports shipped to China in 2017, answers include 15%, 30%, 45%, 60%, 75%. For MFP payments for soybean producers, answers include \$.01, \$.14, \$.86, \$1.00, and \$1.65/per bushel. Results in columns (1), (2), and (5) are coefficients from OLS regressions. Columns (3) and (4) are marginal effects from probit regressions. We include state fixed effects in all specifications and cluster standard errors at the state level. Standard errors are in the parenthesis. *, **, and *** denote significance level at the 0.1, 0.05, and 0.01 level, respectively.

Media and Behavior

Table 5 and Table A3 in the Appendix present the role of media exposure on farmers' actual behavior in 2018 and planned behavior regarding soybeans in 2019, respectively. In Table 5 and Table A3, column (1) shows the probit estimation results of whether farmers reduced their soybean storage. Columns (2) and (3) show changes in the share of farmland planted to soybeans and corn, respectively. Columns (4) and (5) show changes in soybeans marketed pre-, at-, and post-harvest. Column (6) shows changes in soybeans marketed on the non-spot markets.

Table 5. Media Exposure and Farmers' Behavior

	Soybean storage increase (Binary)	Share planted with soybeans	Share planted with corn	Soybeans marketed pre- and at-harvest	Share of soybeans marketed post-harvest	Share of soybeans marketed using non-spot markets
	Probit	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Log of soybean production in 2018	0.032	0.147***	-0.187***	-0.013	0.013	-0.008
	(0.032)	(0.020)	(0.017)	(0.020)	(0.020)	(0.017)
Log of corn production in 2018	-0.048	-0.155***	0.183***	0.025	-0.025	0.011
	(0.034)	(0.018)	(0.018)	(0.023)	(0.023)	(0.017)
Exposure to conservative media (Dummy)	-0.019	0.007	-0.005	0.017	-0.017	0.001
	(0.023)	(0.007)	(0.009)	(0.019)	(0.019)	(0.012)
Exposure to liberal media (Dummy)	0.031	0.004	-0.005	0.030	-0.030	0.013
	(0.025)	(0.011)	(0.011)	(0.021)	(0.021)	(0.016)
Exposure to farm-related media (Dummy)	-0.036	-0.000	-0.007	0.009	-0.009	0.012
	(0.023)	(0.009)	(0.009)	(0.017)	(0.017)	(0.012)
Age	0.001	0.001	0.000	-0.000	0.000	-0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Have some college (Dummy)	-0.0001	-0.011	-0.010	0.004	-0.004	-0.004
	(0.027)	(0.009)	(0.008)	(0.019)	(0.019)	(0.011)
Male	--[a]	-0.006	0.015	0.019	-0.019	0.014
		(0.015)	(0.013)	(0.053)	(0.053)	(0.011)
Risk preference (from 1 to 7)	0.008	0.008**	0.006*	0.012	-0.012	0.002
	(0.009)	(0.003)	(0.003)	(0.007)	(0.007)	(0.005)
Log of farm income	0.02	0.008	-0.000	0.004	-0.004	0.002
	(0.019)	(0.005)	(0.004)	(0.012)	(0.012)	(0.008)
Have livestock (Dummy)	0.024	-0.007	-0.008	-0.009	0.009	-0.009
	(0.023)	(0.008)	(0.008)	(0.018)	(0.018)	(0.013)
Have off-farm income (Dummy)	0.0003	-0.005	0.001	0.017	-0.017	-0.007
	(0.028)	(0.010)	(0.008)	(0.020)	(0.020)	(0.013)
Log of farmland cash rents	0.000	0.000	0.000	0.000	-0.000	-0.000

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	456	472	472	472	472	472

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 also include control variables as specified in equation (3) and omit their coefficients from the table for readability. We include state fixed effects in all specifications and cluster standard errors at the state level. Standard errors are in parentheses. *, **, and *** denote significance level at the 0.1, 0.05, and 0.01 level, respectively

a. Coefficient dropped because of perfect collinearity.

The coefficients for control variables, when statistically significant, have the expected signs. For example, more soybean (corn) production leads to a significantly higher share of land allocated to soybeans (corn) (Columns (2) and (3)), which shows persistency in crop choice across years. We also find that farmers with higher risk tolerance continue to produce affected crops (Column (2)), and farmers exposed to farm-related media are more likely to use non-spot marketing tools (Table A3, Column (6)).

However, we find no statistically significant ($P<0.05$) association between media exposure and farmers' economic decisions related to soybean production and marketing in 2018. While it is possible that farmers have committed to some the economic decisions in 2018, media exposure also has small and statistically insignificant effect for planned behaviors in 2019. These findings fail to reject the null hypotheses H0f-H0i. Though the lack of statistical power could cause each individual behavior, the absence of statistically significant results in all behavioral aspects suggests that media exposure has a weak, if not non-existent, association with actual economic behavior. When examining the confidence intervals, we find that the effects of exposure to conservative and liberal media are practically small for most of the outcomes. Take the estimated impact of conservative media exposure on the probability of soybean storage increase in 2018 in Table 5 Column (1) as an example. The 95% confidence interval for the probability of soybean storage increase is -0.042-0.004. Thus, the relative effect could be anywhere between a 4.2% decrease and a 0.4% increase with a 95% probability.

Combining the previous findings—that political bias has a significant association with farmers' perceptions of income loss from the trade war and the usefulness of the MFP payments—with the findings from this section—that political bias has a limited role in farmers' actual crop storage, planting, and marketing behavior—our analysis shows that partisan bias is only present in stated perceptions but not in behavior.

Additional Robustness Checks

We check the robustness of our results in several ways. We first check the robustness of the results using the share of conservative, liberal, and neutral media as alternative media exposure measurements. Tables A4 in the Appendix present the estimated effects of alternative media exposure on farmers' beliefs and behavior, respectively. The main findings remain robust—media exposure is associated with farmers' beliefs but has a limited role in farmers' behavior. Second, we check the robustness of the results by keeping observations with missing control variables in the analysis by filling in missing values with sample average (Little and Rubin 2019). The signs and magnitude of the coefficient of media exposure are robust, although the coefficients are less statistically significant than those in the main analysis. Some media classifications in the main analysis are based on expert opinion. We also conduct a robustness check with all media sources that require expert judgment (i.e., those not available from Pew

Research Center) categorized as neutral. This alternative classification does not qualitatively change the results on conservative and liberal media. These detailed results for the second and third robustness checks are available upon request.

Discussion and Conclusions

Based on a survey of 472 farmers in three Midwestern states, we investigate the correlation between exposure to conservative, liberal, and neutral media and farmers' perceptions, knowledge, and behavior with respect to the trade dispute between the United States and China. Though we base our results on media exposure, we argue that the relationships between media exposure and perceptions and behavior are indicative of the relationships between political attitudes and these perceptions and behavior.

We find that exposure to conservative (liberal) media is associated with a reduction (increase) in farmers' expected income loss from the trade war and an increase (decrease) in their beliefs that MFP payments are helpful. These findings suggest that perceptions of economic conditions are still subject to the partisan screen even when financial interest is directly involved. Furthermore, the differences in economic perspective are partially caused by disagreements about fundamental facts. People who control the means of production and whose own financial interest is at stake are more likely to seek accurate information. However, our results suggest that such information seeking cannot eliminate the effects of partisan bias in shaping economic perceptions.

In contrast to the strong correlation between media exposure and farmers' perceptions and perceived helpfulness of government payments, we find little correlation between media exposure (and, by extension, political attitudes) and economic decisions. Though the lack of statistical power could cause the null results, the absence of statistically significant effects in all behavior aspects under study suggests that political attitudes have weak effects, if any, on economic behavior. The null results on economic behavior suggest that the potentially biased information received by conservative and liberal farmers is not the decisive factor in creating partisan bias, and farmers with different political attitudes make similar economic decisions. The inconsistency between stated perceptions and behavior here adds weight to the argument survey responses about economic beliefs are subject to cheerleading. Our results go further than the previous literature to show that such cheerleading exist even in expectations regarding one's own economic conditions.

While the results supports cheerleading, it does not necessarily jeopardize the usefulness of the survey instrument. Since cheerleading may exist in other domains, such as voting, partisan differences in survey responses may well predict other important behaviors, even though they cannot predict economic decisions. In fact, Donovan et al. (2019) find that presidential approval is increasingly detached from economic perceptions. An important question for future research is which domains of behavior are influenced by cheerleading.

If partisanship does not entirely drive economic perceptions, tariffs applied by China and MFP payments applied by the United States on US farmers would have been effective. We find evidence that farmers' economic perception does depend on economic realities—that is, farmers who produce more soybeans expect heavier loss and perceive MFP subsidies as more helpful. Therefore, our findings suggest that both economic factors and political bias shape farmers' economic perceptions, and their production and marketing behavior are less likely associated with political bias.

This study has several limitations, and thus future studies can improve upon ours. This study relies on the effects of media exposure to infer the effects of political attitudes on economic perceptions and behavior. 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 base the lack of statistically significant association between media exposure and farming and marketing behavior on modest sample size, and future studies can use a larger sample or field experiments to explore the perception-behavior link more extensively.

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.

Balistreri, Edward J., 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*, 2020(Winter), 1.

Bartels, Larry M. 2002. "Beyond the Running Tally: Partisan Bias in Political Perceptions." *Political Behavior* 24(2): 117-50.

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

Bolsen, Toby, and Risa Palm. .2019. "Motivated Reasoning and Political Decision Making." In *Oxford Research Encyclopedia of Politics.*

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.

Bullock, John, Alan Gerber, Seth Hill, and Gregory Huber. 2015. "Partisan Bias in Factual Beliefs about Politics." *Quarterly Journal of Political Science* 10(4): 519-78.

Campbell, Angus, Phillip E. Converse, Warren E. Miller, and Donald E. Stokes. 1960. *The American Voter*. New York: Wiley.

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.

Cleveland, William. S. 1981. "LOWESS: A Program for Smoothing Scatterplots by Robust Locally Weighted Regression." *American Statistician* 35(1): 54.

Donovan, K., Kellstedt, P. M., Key, E. M., & Lebo, M. J. 2020. "Motivated reasoning, public opinion, and presidential approval." *Political Behavior*, *42*(4), 1201-1221.

Evans, Geoffrey, and Robert Andersen. 2006. "The Political Conditioning of Economic Perceptions." *American Journal of Political Science* 68 (1): 194-207.

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.

Flynn, D.J., Brendan Nyhan, and Jason Reifler. 2017. "The Nature and Origins of Misperceptions." *Political Psychology* 38(S1): 127-50.

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.

Glauber, Joseph W. 2019. *Agricultural Trade Aid: Implications and Consequences for US Global Trade Relationships in the Context of the World Trade Organization*. Washington, DC: American Enterprise Institute.

Hamlin, Alan, and Colin Jennings. 2011. "Expressive Political Behaviour: Foundations, Scope and Implications." *British Journal of Political Science* 645-670.

Hoewe, Jennifer, and Cynthia Peacock. 2020. "The Power of Media in Shaping Political Attitudes." *Current Opinion in Behavioral Sciences* 34: 19-24.

Jamieson, Kathleen Hall, and Joseph N. Cappella. 2008. *Echo chamber: Rush Limbaugh and the conservative media establishment*. Oxford: Oxford University Press.

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

Jerit, Jennifer, and Jason Barabas. 2012. "Partisan Perceptual Bias and the Information Environment." *Journal of Politics* 74(3): 672-84.

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.

Kim, J. W., & Kim, E. 2021. “Temporal Selective Exposure: How Partisans Choose When to Follow Politics.” *Political Behavior*, *43*(4), 1663-1683.

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

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.

Little, Roderick J.A., and Donald B. Rubin. 2019. *Statistical Analysis with Missing Data*, Vol. 793. New York: John Wiley & Sons.

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) (2017): 363-83.

Mitchell, Amy, Jefferey Gottfried, Jocelyn Kiley, and Katerina Eva Matsa. 2014. “Political Polarization & Media Habits.” Pew Research Center. Retrieved June 22, 2021 (https://www.journalism.org/2014/10/21/political-polarization-media-habits/).

Peterson, Erik, and Shanto Iyengar. 2021. “Partisan Gaps in Political Information and Information-Seeking Behavior: Motivated Reasoning or Cheerleading?” *American Journal of Political Science* 65(1): 133-147.

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

Prior, Markus, Gaurav Sood, and Kabir Khanna. 2015. "You Cannot be Serious: The Impact of Accuracy Incentives on Partisan Bias in Reports of Economic Perceptions." *Quarterly Journal of Political Science* 10(4): 489-518.

Redlawsk, David P., Andrew J.W. Civettini, and Karen M. Emmerson. 2010. "The Affective Tipping Point: Do Motivated Reasoners Ever "get it"?" *Political Psychology* 31(4): 563-593.

Schuessler, Alexander A. 2000. "Expressive Voting." *Rationality and Society* 12(1): 87-119.

Shapiro, Robert Y., and Yaeli Bloch-Elkon. 2008. "Do the Facts Speak for Themselves? Partisan Disagreement as a Challenge to Democratic Competence." *Critical Review* 20(1-2): 115-139.

Shonkwiler, J.S., and G.S. Maddala. 1985. "Modeling Expectations of Bounded Prices: An Application to the Market for Corn." *The Review of Economics and Statistics* 697-702.

Stanig, Piero. 2013. "Political Polarization in Retrospective Economic Evaluations during Recessions and Recoveries." *Electoral Studies* 32(4): 729-45.

Taber, Charles S., and Milton Lodge. 2006. "Motivated Skepticism in the Evaluation of Political Beliefs." *American Journal of Political Science* 50(3): 755-69

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

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.

Supplemental Information

Partisan bias in Statements Versus Behavior: Evidence from Farmers' Reactions to the US-China Trade War

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

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 matters in the soil (Hall, Russell, and Moore 2019). If a farmer decides to decrease soybean planting, they can take acres out from 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 the 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 grains 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 to have 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:

$$\text{Cash price} = \text{futures price} + \text{basis}$$

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. 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 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 physically deliver the crop. 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 for the Appendix

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 Tables

Table A1. Summary Statistics of Farmers' frequently used Media Sources

Type	Media	Mean	Standard error	Min	Max
Conservative	Farm Bureau	0.326	0.469	0	1
	Fox News	0.286	0.452	0	1
	National State Corn Growers	0.015	0.121	0	1
	National State Soybean Association	0.004	0.065	0	1
Liberal	CNN	0.108	0.311	0	1
	WSJ	0.076	0.266	0	1
	NPR	0.025	0.158	0	1
	CBS	0.021	0.144	0	1
	MSNBC	0.015	0.121	0	1
	NBC	0.017	0.129	0	1
	Bloomberg	0.013	0.112	0	1
	PBS	0.013	0.112	0	1
	ABC	0.004	0.065	0	1
	CNBC	0.006	0.080	0	1
	Cedar Rapids Gazette	0.002	0.046	0	1
Farm-related outlets	Successful Farming	0.316	0.465	0	1
	USDA	0.269	0.444	0	1
	Extension	0.189	0.392	0	1
	Farm Magazines	0.038	0.192	0	1
	Farm Journal	0.034	0.181	0	1
	Ag Web	0.032	0.176	0	1
	DTN	0.025	0.158	0	1
	RFD	0.023	0.151	0	1
	WNAX Radio	0.008	0.092	0	1
	Pro Farmer	0.013	0.112	0	1
	Iowa Farmer Today	0.013	0.112	0	1
	Wallaces Farmer	0.015	0.121	0	1
	Agri-talk Radio	0.011	0.102	0	1
	Roach Ag	0.008	0.092	0	1
	Progressive Farmer	0.004	0.065	0	1
	Linder Farmer Network	0.004	0.065	0	1
	WHO	0.025	0.158	0	1

Notes: We classify media sources into three categories—conservative, liberal, and neutral. Classification of conservative and liberal is from a Pew Research Center report on the ideological placement of each media's audience (Mitchell et al. 2014) and opinions from farm management specialists. We exclude Facebook and Twitter from the analysis because it is hard to determine the political inclination of the news that farmers consume on these platforms.

Table A2. Marginal Impacts of Media Exposure on Probabilities of Beliefs on Expected Income Loss and Perceived MFP Payments Helpfulness using Ordered Probit Model

	Conservative			Liberal			Farm-related		
Variables	Coef.	s.e.	Significance level	Coef.	s.e.	Significance level	Coef.	s.e.	Significance level
Panel A: Outcome: Expected income loss									
1: up >20%	0.80%	0.004	0.06	-0.81%	0.004	0.07	-0.46%	0.004	0.22
2: up 10–20%	0.63%	0.003	0.07	-0.63%	0.004	0.14	-0.36%	0.003	0.23
3: up 5–10%	0.19%	0.002	0.22	-0.19%	0.002	0.25	-0.11%	0.001	0.33
4: up <5%	0.37%	0.002	0.13	-0.37%	0.003	0.15	-0.21%	0.002	0.25
5: No change	1.86%	0.009	0.03	-1.87%	0.010	0.06	-1.07%	0.008	0.18
6: Down <5%	1.25%	0.006	0.04	-1.26%	0.007	0.07	-0.72%	0.005	0.19
7: Down 5–10%	3.08%	0.014	0.02	-3.10%	0.016	0.05	-1.77%	0.013	0.18
8: Down 10–20%	0.13%	0.005	0.77	-0.13%	0.005	0.77	-0.08%	0.003	0.78
9: Down 20%	-8.31%	0.035	0.02	8.36%	0.041	0.04	4.78%	0.035	0.17
Panel B: Outcome: MFP payments are helpful									
1: Not at all helpful	-3.68%	0.012	0.00	1.35%	0.011	0.23	0.76%	0.010	0.46
2: Not sure	-3.14%	0.010	0.00	1.15%	0.009	0.22	0.65%	0.009	0.47
3: Somewhat helpful	-7.37%	0.021	0.00	2.70%	0.023	0.23	1.52%	0.021	0.46
4: Quite helpful	2.24%	0.007	0.00	-0.82%	0.007	0.23	-0.46%	0.006	0.47
4: Very helpful	11.95%	0.033	0.00	-4.38%	0.036	0.23	-2.47%	0.033	0.46

Table A3. Media Exposure and Farmers' Planned Behavior in 2019

-	Soybean storage increase (Binary)	Share planted with soybeans	Share planted with corn	Soybeans marketed pre- and at-harvest	Share of soybeans marketed post-harvest	Share of soybeans marketed using non-spot markets
	Probit	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Log of soybean production in 2018	0.040	0.004	-0.038	-0.008	0.008	0.000
	(0.026)	(0.027)	(0.027)	(0.021)	(0.021)	(0.016)
Log of corn production in 2018	-0.040	-0.014	0.028	0.005	-0.005	-0.004
	(0.029)	(0.027)	(0.027)	(0.022)	(0.022)	(0.014)
Exposure to conservative media (Dummy)	-0.013	-0.008	-0.013	0.017	-0.017	-0.004
	(0.026)	(0.014)	(0.016)	(0.018)	(0.018)	(0.014)
Exposure to liberal media (Dummy)	0.022	-0.009	0.030*	0.006	-0.006	-0.007
	(0.028)	(0.016)	(0.017)	(0.025)	(0.025)	(0.017)
Exposure to farm-related media (Dummy)	0.012	-0.006	0.014	0.008	-0.008	0.032**
	(0.025)	(0.014)	(0.016)	(0.021)	(0.021)	(0.014)
Age	-0.001	-0.001	-0.001	0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Have some college (Dummy)	-0.025	-0.018	0.029*	0.007	-0.007	-0.017
	(0.028)	(0.016)	(0.016)	(0.019)	(0.019)	(0.013)
Male	0.012	-0.052	-0.047	0.029	-0.029	0.023
	(0.082)	(0.032)	(0.034)	(0.074)	(0.074)	(0.019)
Risk preference (from 1 to 7)	0.010	0.008	0.002	0.005	-0.005	-0.003
	(0.009)	(0.005)	(0.006)	(0.008)	(0.008)	(0.006)
Log of farm income	0.028	0.003	0.004	0.009	-0.009	-0.001
	(0.017)	(0.008)	(0.010)	(0.013)	(0.013)	(0.007)
Have livestock (Dummy)	-0.012	-0.042***	-0.019	-0.003	0.003	0.001
	(0.270)	(0.013)	(0.015)	(0.021)	(0.021)	(0.013)
Have off-farm income (Dummy)	0.026	0.027*	-0.013	0.013	-0.013	-0.024
	(0.029)	(0.015)	(0.014)	(0.022)	(0.022)	(0.015)
Log of farmland cash rents	0.0001	0.000	-0.000	-0.000	0.000	-0.000

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	470	472	472	472	472	472

Notes: This table presents the impact of media exposure on farmers' soybean storage, soybean and corn planting behavior, and marketing behavior in 2019. Column (1) presents marginal effects estimated with probit, and we estimate columns (2)–(6) with OLS. We also include control variables as specified in equation (3) and omit their coefficients from the table for readability. We include state fixed effects in all specifications and cluster standard errors at the state level. Standard errors are in parentheses. *, **, and *** denote significance level at the 10%, 5%, and 1% level, respectively

Table A4. Media Exposure and Farmers' Behavior with Alternative Exposure Measures

	Soybean storage increase (Binary)	Share planted with soybeans	Soybeans marketed pre- and at-harvest	Share of soybeans marketed post-harvest	Share of soybeans marketed using non-spot markets
-	Probit	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)
Behavior in 2018					
Exposure to conservative media (Share 0–1)	-0.102	0.022	0.013	-0.013	-0.025
	(0.095)	(0.041)	(0.120)	(0.120)	(0.049)
Exposure to liberal media (Share 0–1)	-0.032	0.025	0.027	-0.027	-0.010
	(0.097)	(0.047)	(0.125)	(0.125)	(0.051)
Exposure to farm-related media (Share 0–1)	-0.133	0.018	0.005	-0.005	-0.012
	(0.097)	(0.042)	(0.123)	(0.123)	(0.052)
Number of observations	470	472	472	472	472
Behavior in 2019					
Exposure to conservative media (Dummy)	-0.098	-0.047	-0.093*	0.093*	-0.011
	(0.094)	(0.054)	(0.053)	(0.053)	(0.045)
Exposure to liberal media (Dummy)	-0.019	-0.036	-0.117*	0.117*	-0.027
	(0.097)	(0.057)	(0.063)	(0.063)	(0.044)
Exposure to farm-related media (Dummy)	-0.040	-0.052	-0.114**	0.114**	0.025
	(0.094)	(0.054)	(0.050)	(0.050)	(0.045)
Observations	470	472	472	472	472

Notes: This table checks the robustness of results in table 5 using the share of different media types to measure media exposure. Column (1) presents marginal effects estimated with probit, and we estimate columns (2)–(5) with OLS. We also include control variables specified in equation (3) and omit their coefficients from the table for readability. Standard errors are in the parenthesis. *, **, and *** denote significance at the 10, 5, and 1% levels, respectively.