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Political Bias, Media, and Midwest Farmers' Reactions to the U.S.-China Trade War

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Selected Paper prepared for presentation at the 2021 Agricultural & Applied Economics Association Annual Meeting, Austin, TX, August 1 – August 3

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

JEL codes: D83; D84; Q13; Q18

Acknowledgments: 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 the USDA National Institute of Food and Agriculture (NIFA) Hatch Project 1010309. The authors also thank Chad Hart, Nate Cook, Guang Han, Jonathan Hassid, Kelvin Leibold, and Yang Xie for feedback on earlier drafts.

Abstract: U.S. farmers bear the brunt of the U.S.-China trade war in 2018 initiated by a Republican administration that most farmers support. Analyzing a 2019 farmer survey in the Midwest, we find that frequent use of conservative (liberal) media is associated with a 2.3% decrease (2.4% increase) in farmers' expected income loss and a 14.3% increase in the probability of perceiving Market Facilitation Program payments as helpful. Viewers of different media sources disagreeing on facts including the level of tariffs and the share of soybeans exported to China could partially explain the discrepancy in expected income impacts. We find little evidence for the association between media exposure and farmers' economic decisions. These results indicate that farmers' political attitudes are strongly associated with their economic perceptions but have weaker or no association with their behaviors. While previous studies find political bias in the perceptions of general economic conditions, we show that political attitudes also affect economic perceptions when people's financial interest is directly affected.

Political Bias, Media, and U.S. Midwest Farmers' Reactions to the U.S.-China Trade War

Introduction

There is a longstanding literature documenting how the "partisan screen" (Campbell et al. 1960, 133) filters realities. In other words, people's perceptions of realities (Bullock and Lenz 2019; 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. Such partisan perceptions only partially converge when economic facts are clear enough (Redlawsk et al. 2010) and when rewards are provided for accurate answers (Bullock et al. 2015; Peterson and Iyengar 2021; Prior et al. 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; Schuesseler, 2000). A limited number of studies (Gerber and Huber 2009; Gerber and Huber 2010; McGrath 2017) that look at people's behaviors find that people do not always behave according to their reported perceptions (McGrath 2017), suggesting that such perceptions may be a form of partisan cheerleading rather than sincere beliefs. Because existing studies primarily focus on perceptions of general economic conditions, it is unclear what happens when people's financial interest is directly affected. In these cases, would people's economic perceptions still be affected by their political views? Would individuals act upon their perceptions? This study aims to shed light on these questions by studying how Midwest farmers perceive the economic impacts of the ongoing U.S.-China trade war and how their production and marketing decisions change as a result.

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

The U.S.-China trade conflict offers a unique condition for our investigation. First, China's retaliatory tariffs and U.S. MFP payments created large and relatively predictable shocks on farmers' income. Therefore, one can consider the differences in perceived trade war impacts as the results of different political views after controlling crop production and other relevant farm characteristics. Second, farmers' anticipation of future economic conditions has behavior implications, which allows us to examine the consistency between perceptions and behaviors. Specifically, if farmers expected soybean prices to decline due to the trade war, they would likely decrease storage and planting acres and increase pre-harvest sales (Kadjo et al. 2018). Furthermore, if farmers expected higher risk, they likely would increase the use of hedging tools such as futures, options, and other grain contracts (MacDonald 2020).

In recent years, the partisan screen has been reinforced by the increasingly polarized media landscape, with liberal and conservative media casting the same events, including the trade war, in drastically different lights. Partisan media may cause audiences to be more polarized in two ways. On the one hand, consuming different media sources with different political leanings may influence audience attitudes (Hoewe and Peacock 2020), causing them to be more partisan in general and disagree more on particular issues such as the trade war. On the other hand, because audiences tend to select media sources that conform with their views (Peterson and Iyengar 2021), media polarization may change audience composition. As a result, people with similar political inclinations increasingly congregate around the same media sources. These two mechanisms create an echo chamber that enhances the political alignment of audiences of the same media and widens the gap between audiences of different media (Jamieson and Cappella 2008). This study focuses on how farmers' economic perceptions and behaviors differ by whether they consume 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 behaviors. This interpretation is bolstered by the fact that in our data most farmers either use liberal or conservative media exclusively as their most frequent sources.

Our data were collected 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 U.S. agricultural cash receipts and 11.1% of U.S. 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 2014) and the 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 the tariff rate on soybean, the share of soybean exported to China, and MFP payment rate for soybean producers; and (*c*) economic decisions about soybean storage, planting, and marketing. Because the outcomes include continuous, interval, and dummy variables, we use the Ordinary Least Square regression (OLS), interval regression, and Probit models, respectively.

We report three findings. First, we find that media exposure does affect economic perception. Frequent exposure to conservative media is associated with a 2.3% decrease in farmers' expected income loss while frequent exposure to liberal media is weakly ($p<10\%$) associated with a 2.4% decrease in farmers' expected income loss. The implied gap in expected income loss is 4.7% between farmers who only list liberal versus 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, this gap of 4.7% is relatively large and economically significant ($30,810). Also, frequent exposure to conservative media is associated with a 14.3% increase in the probability of farmers perceiving MFP payments as helpful, while 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, we explore whether the differences in economic perceptions stem from disagreements in basic facts. When asked about China's tariff rate on U.S. soybeans (25%) and the percent of U.S. soybean export going 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. In other words, people who consume different media sources do disagree on basic facts, and the consumers of conservative media believe in facts that diminish the impacts of the trade war.

Third, we find little association between media exposure and farming and marketing behaviors. For soybeans, the most affected commodity, neither liberal nor conservative media has any statistically significant impact on storage, planting, pre-harvest versus post-harvest marketing, and the utilization of spot versus non-spot markets in 2018 or 2019. While the lack of behavioral responses in individual outcomes may be caused by imprecise estimation, 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, adding 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), we show that the partisan screen is likely at work even when a policy directly affects individuals' economic conditions. The partisan differences in economic perceptions at least partially stem from disagreements in basic facts. Second, the article contributes to the literature on political bias and perception-behavior consistency (Gerber and Huber 2009; Gerber and Huber 2010; McGrath 2017). We find no statistically significant evidence that political bias extends to actual behaviors, which adds weight to the partisan cheerleading argument.

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. We selected 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, 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 (the main outcome of interest) and other important farm characteristics that affect the main outcome of interest, 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]

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?" We classify the reported media outlets into three categories—conservative, liberal, and neutral. The conservative and liberal media sources are first classified based on the ideological placement of each media outlet's audiences from a study by the Pew Research Center (Mitchell 2014). For local and farm-related media sources not covered by the Pew Research Center study, we determine the liberal/conservative classification based on the expert opinions of farm management specialists from Iowa State University Extension. Media sources not covered by the Pew Research Center study and not recognized by experts as partisan are categorized as "Neutral" media sources.[5] As 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%).

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 are farmers' knowledge of Chinese tariffs on U.S. soybean, China's share in U.S. soybean export, and the level of MFP payments for soybeans. The knowledge questions have choices that are too low, correct, 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 behaviors include the shares of soybeans marketed in spot and non-spot markets, and pre and at-harvest or post-harvest.

Summary Statistics

Table 2 presents summary statistics of the main variables used in our analysis. Farmers sought information about the U.S.-China trade conflict 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%) farmers used liberal and conservative media simultaneously while 66.7% of farmers 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 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%.

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 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 U.S. soybeans, 64.2% of farmers answer the question correctly, while 21.3% and 14.5% of farmers choose numbers that are too low and too high, respectively. On the question of what percentage of U.S. soybean export goes to China, 34.3% of farmers answer the question correctly, while 58.0% and 7.7% of farmers underestimate or overestimate. On the question of MFP payment rate for soybean producers, 92.3% of farmers answer the question correctly ($1.65 per bushel), while 7.7% of farmers underestimate.

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

Empirical Methods

Basic Model

The basic 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 (farm-related) media, respectively. In the main analysis, we use dummies to measure media exposure. Specifically, $Cons_{ics}$ ($Lib_{ics}, and\ Neu_{ics}$), equals 1 if a farmer listed at least one conservative (liberal, neutral/farm-related) media outlet as a frequent information source, 0 otherwise. It is worth noting that exposure to conservative, liberal, and neutral media is not exclusive (i.e., farmers can use two or three media types with different political orientations frequently). 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 comprehensive 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. The cash rent is estimated by multiply the county-level cash rent for irrigated cropland by the share of rented land. State fixed effects, FE_s, are included 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. For continuous variables, we use OLS; for categorical variables representing intervals, we use interval regression (Billard and Diday 2000); and, for ordinal variables, we use both probit and ordered probit models and report average marginal effects (Long 1997).

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. 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, which reflects the impact of the trade war. Thus, we construct the first measurement of farmer i's real income loss as:

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

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 U.S. soybean exports to China declined by $1.38/bushel, while 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 associate with the gap between farmer's expected and actual income loss from the trade war, we construct the following measurement:

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

where Exp_{ic} denotes farmers' self-reported percentage-of-income impact from the trade war, and $\frac{RealLoss_{ic}}{Income_{ic}}$ 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). In the 2018 MFP payments, the payment rate was \$0.01/bushel for corn and \$1.65/bushel for soybeans. Since the estimated actual losses according to the second method are higher than farmers' expected income loss, it is possible that farmers overlooked survey instruction 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

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.

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. Interval regression results in column (1) show that farmers who are frequently exposed to conservative media report a lower expected income loss (2.3%). 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. 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. The consumers of conservative media are more optimistic about the trade war impacts on their income while the consumers of liberal media are more pessimistic.

Results in column (6) indicate that frequent use of conservative media increases farmers' belief that MFP payments are 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 the farmers find MFP payments helpful is therefore 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 A1 in the Appendix presents the estimated marginal impacts. The main findings remain robust.

Notably, farmers who produce more soybeans expect more income loss (Table 3, Column (1)) and are more likely to believe that MFP payments are helpful (Table 3, Column (6)). These are expected results considering that both China's retaliatory tariffs and U.S. MFP payments target soybeans. It shows that despite 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 stronger beliefs that MFP payments are helpful. Liberal media exposure, on the other hand, is associated with higher expected income loss and weaker beliefs that MFP payments are helpful. 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 partisan screen is also at work when a policy directly affects individuals' economic conditions.

Knowledge of the 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 U.S. soybean exports shipped to China in 2017 (60%), and the MFP payment rate for soybean producers ($1.65 per bushel). We use OLS regression and regress farmers' answers in percentage on media exposure and control variables. We find that the frequent exposure to conservative media is associated with a 1.4% (table 4, column 1) lower tariff rate estimate and 2.5% (table 4, column 2) lower export share estimate. Both associations are statistically significant at the 10% level. Column 3 Table 4 shows that exposure to conservative media is associated with a statistically insignificant 3% higher MFP soybean payment rate. The lack of statistical significance in MFP results is not surprising because MFP was just announced at the time of the survey and the vast majority of farmers knew the correct answer. Since tariff rate and export share to China are positively related to the severity of trade war impacts, these findings indicate that farmers who are exposed to conservative media perceive facts in a way that diminishes trade war impacts. This is a potential explanation for why media exposure associates with biased expected income loss.

Media and Behavior

Panels A and B in table 5 present the role of media exposure in farmers' actual behaviors in 2018 and planned behaviors in 2019, respectively. Column (1) shows the probit estimation results as to whether farmers reduced their soybean storage. Columns (2) and (3) show changes in farmland planted to soybeans and corn, respectively. Columns (4) and (5) show changes in soybeans marketed pre-, at-, and post-harvest. Columns (6) and (7) show changes in soybeans marketed on the spot and non-spot markets, respectively.

Overall, we find no statistically significant association between media exposure and farmers' economic decisions related to soybean production and marketing in 2018 or 2019. For most of the outcomes the effects of exposure to conservative and liberal media are practically small and in the same direction. While each individual null result could be caused by the lack of statistical power, the absence of statistically significant results in all behavioral aspects suggests that media exposure has weak, if not non-existent, association with actual economic behaviors.

Combining the findings from the previous section 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 adds weight to the argument that stated economic expectations reflect partisan cheerleading instead of genuine belief.

Additional Robustness Checks

We check the robustness of the 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 A3 and A4 in the Appendix present the estimated results of alternative media exposure on farmers' beliefs and behaviors, respectively. The main findings remain robust—media exposure is associated with farmers' beliefs but has a limited role in farmers' behaviors. 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 judgement (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 and behaviors with respect to the trade dispute between the U.S. and China. While the results are based on media exposure, we argue that the relationships between media exposure and perceptions and behaviors are indicative of the relationships between political attitudes and these perceptions and behaviors. We make this argument because media exposure can be linked to political attitudes through several potential mechanisms. First, audiences congregate around media sources that align with their political dispositions. Therefore, whether a farmer consumes conservative or liberal media sources can be a proxy of whether he/she holds prior conservative or liberal views. In our study, we find support for this mechanism in that most farmers consume liberal or conservative media exclusively. Second, exposure to different media sources may change the partisan attitudes of its audiences, which, in turn, affect the audience members' perceptions and behaviors. The media effects in this mechanism depend on partisan attitudes influencing perceptions and behaviors. Third, media exposure may directly change perceptions on specific issues without changing people's general partisan attitudes. Since people with similar political attitudes tend to consume similar media sources, this persuasion effect on specific issues would still create an association between political alignment and economic perceptions.

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 when one's financial interest is directly involved, perceptions of economic conditions are still subject to the partisan screen. Furthermore, the differences in economic perspective are at least partially caused by disagreements about fundamental facts. When their own financial interest is at stake, people are 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. While the null results could be caused by the lack of statistical power, the absence of statistically significant effects in all behavior aspects under study suggests that political attitudes have weak effects, if any, on economic behaviors. Since previous studies show that farmers do respond to genuine expectations (Choi and Helmberger 1993; Shonkwiler and Maddala 1985), the inconsistency between stated perceptions and behaviors here adds weight to the argument that stated economic expectations developed due to "partisan cheerleading" and do not reflect sincere beliefs.

If economic perceptions are not entirely driven by partisanship, tariffs applied by China and MFP payments applied by the United States on U.S. 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 to be more helpful.

Therefore, our findings suggest that farmers' economic perceptions are shaped by both economic factors and political bias, while their production and marketing behaviors are less likely to be associated with political bias.

This study has several limitations that can be improved in future studies. This study relied on the effects of media exposure to infer the effects of political attitudes on economic perceptions and behaviors. As a result, the relationships we discovered are qualitative in nature. 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, the lack of statistically significant association between media exposure and farming and marketing behaviors is based on a modest sample size, and futures studies can use a larger sample or field experiments to explore the perception-behavior link more extensively.

Endnotes

1 USDA distributed 2018 MFP payments during the period of data collection. The MFP payments for 2019 had not been finalized at the time of the survey and were not asked.

2 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.

3 We test whether there is a selection problem in missing answers to the question on expected income loss from the U.S.-China trade war in 2018 and find no correlation between the probability of a missing answer and farmers' various demographic characteristics (education, age) and farming attributes, such as soybean and corn planted acreage in 2018.

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

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

6 Soybean is the most seriously affected agricultural commodity in the trade war. China imposed a 25% tariff on U.S. soybeans on July 7, 2018, and an additional 5% tariff on September 1, 2019.

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

8 We code scale 1 (up more than 20%) as -25%, and scale 9 (down more than 20%) as 25%.

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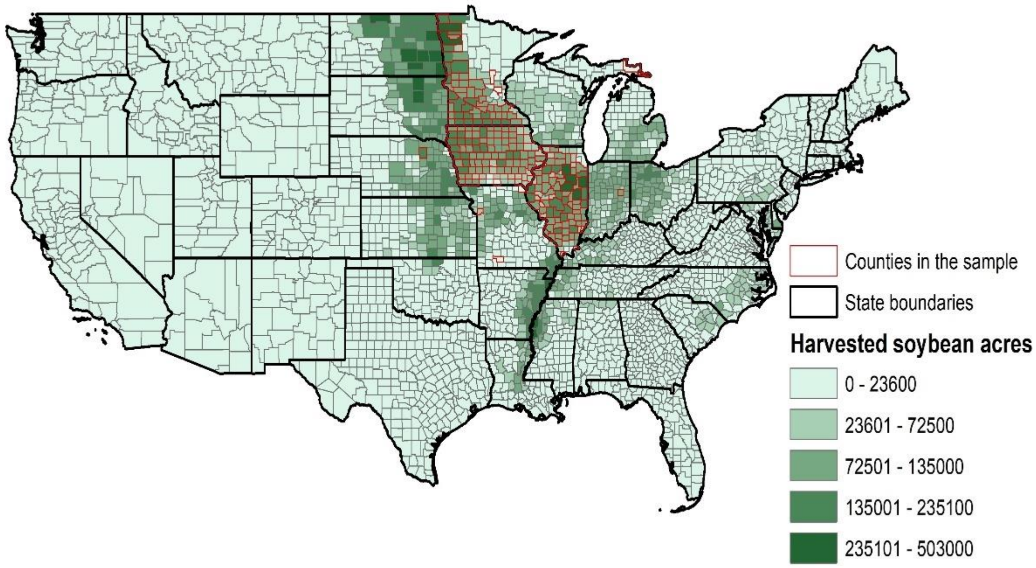

Figure 1. Overlap of counties included in our sample and county-level soybean planted acres.

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. While most respondents' primary farm operations are in Iowa, Illinois, and Minnesota, several respondent's primary farm operations are located in other states.

Table 1. Selected Survey Questions of Main Interest

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)
Behaviors		
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? (Each entry should be between 0–100; each column should add to 100.)	Continuous variable from 0-1
Knowledge of the U.S. soybean market		
	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%

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

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
Beliefs				
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
Behaviors				
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
Knowledge of U.S. soybean market				
Knowledge of percent of tariff the Chinese government impose 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
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: While 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.

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 irrigated land cash rent*Share of land rented)	-0.006	-0.009	-0.011	-0.003	-0.005	-0.0003
	(0.009)	(0.010)	(0.010)	(0.008)	(0.007)	(0.0004)
Number of observations	472	472	472	472	472	470

Notes: This table presents the estimation results of the role 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 from the trade war. 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 10%, 5%, and 1% level, respectively.

Table 4. Media Exposure and Farmers' Knowledge

	Tariffs China imposed on US soybeans	Share of US soybean exports shipped to China	MFP payment rate for soybean producers
	(1)	(2)	(3)
Log of soybean production in 2018	1.072	1.874	7.387
	(0.897)	(1.714)	(4.563)
Log of corn production in 2018	-0.443	-3.188*	-7.288*
	(0.873)	(1.758)	(3.888)
Exposure to conservative media	-1.371*	-2.548*	3.006
	(0.793)	(1.440)	(2.657)
Exposure to liberal media	0.733	-0.165	-0.640
	(0.779)	(1.915)	(3.400)
Exposure to farm-related media	0.961	2.733*	1.245
	(0.639)	(1.483)	(2.646)
Age	-0.024	-0.114	-0.293*
	(0.030)	(0.078)	(0.158)
Have some college (Dummy)	-1.986***	0.692	-2.871
	(0.748)	(1.651)	(3.155)
Male	-0.350	-5.285	10.549
	(2.574)	(5.450)	(11.244)
Risk preference (from 1 to 7)	0.115	0.749	-0.663
	(0.330)	(0.669)	(1.013)
Log of farm income	-0.569	1.006	2.272
	(0.511)	(1.015)	(1.999)
Have livestock (Dummy)	-0.053	-0.921	-1.654
	(0.833)	(1.570)	(2.756)
Have off-farm income (Dummy)	1.887**	-0.650	2.388
	(0.852)	(1.766)	(3.199)
Log of farmland cash rents	-0.007	0.010	0.008
	(0.006)	(0.012)	(0.022)

Number of observations	456	455	469

Notes: Columns (1)–(3) present OLS estimation of the role of media exposure in farmers' knowledge of China's tariffs on U.S. soybeans, the share of U.S. soybean exports shipped to China in 2017, and the first round MFP payments for soybean producers (For knowledge of China's tariffs, answers include 10%, 15%, 25%, 35%, 45%; For knowledge of the share of U.S. soybean exports shipped to China in 2017, answers include 15%, 30%, 45%, 60%, 75%; For MFP payments for soybean producers, answers include 1, 14, 86, 100, and 165 cents per bushel). 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 10%, 5%, and 1% level, respectively.

Table 5. Media Exposure and Farmers' Behaviors

-	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 spot markets	Share of soybeans marketed using non-spot markets
	Probit	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Behavior in 2018							
Exposure to conservative media (Dummy)	-0.019	0.007	-0.005	0.017	-0.017	-0.001	0.001
	(0.023)	(0.007)	(0.009)	(0.019)	(0.019)	(0.012)	(0.012)
Exposure to liberal media (Dummy)	0.031	0.004	-0.005	0.030	-0.030	-0.013	0.013
	(0.025)	(0.011)	(0.011)	(0.021)	(0.021)	(0.016)	(0.016)
Exposure to farm-related media (Dummy)	-0.036	-0.000	-0.007	0.009	-0.009	-0.012	0.012
	(0.023)	(0.009)	(0.009)	(0.017)	(0.017)	(0.012)	(0.012)
Number of observations	470	472	472	472	472	472	472
Behavior in 2019							
Exposure to conservative media (Dummy)	-0.013	-0.008	-0.013	0.017	-0.017	0.004	-0.004
	(0.026)	(0.014)	(0.016)	(0.018)	(0.018)	(0.014)	(0.014)
Exposure to liberal media (Dummy)	0.022	-0.009	0.030*	0.006	-0.006	0.007	-0.007
	(0.028)	(0.016)	(0.017)	(0.025)	(0.025)	(0.017)	(0.017)
Exposure to neutral media	0.012	-0.006	0.014	0.008	-0.008	-0.032**	0.032**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	(0.025)	(0.014)	(0.016)	(0.021)	(0.021)	(0.014)	(0.014)
Number of observations	470	472	472	472	472	472	472

Notes: This table presents the impact of media exposure on farmers' soybean storage, soybean and corn planting behaviors, and marketing behaviors in 2018 and 2019. Column (1) presents marginal effects estimated with probit, while columns (2)–(7) are estimated 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.

Appendix

"Political Bias, Media, and Midwest Farmers' Reactions to the U.S.-China Trade War"

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
	Wallace 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 (farm-related). Classification of conservative and liberal is from a Pew Research Center report on the ideological placement of each media's audience (Mitchell 2014) and opinions from farm management specialists. We exclude Facebook and Twitter from the analysis because it's hard to tell 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 A4. Media Exposure and Farmers' Behaviors

-	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 spot markets	Share of soybeans marketed using non-spot markets
	Probit	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Behavior in 2018							
Exposure to conservative media (Share 0-1)	-0.102	0.022	0.003	0.013	-0.013	-0.019	-0.025
	(0.095)	(0.041)	(0.035)	(0.120)	(0.120)	(0.042)	(0.049)
Exposure to liberal media (Share 0-1)	-0.032	0.025	0.012	0.027	-0.027	-0.035	-0.010
	(0.097)	(0.047)	(0.043)	(0.125)	(0.125)	(0.043)	(0.051)
Exposure to farm-related media (Share 0-1)	-0.133	0.018	0.000	0.005	-0.005	-0.030	-0.012
	(0.097)	(0.042)	(0.035)	(0.123)	(0.123)	(0.045)	(0.052)
Number of observations	470	472	472	472	472	457	472
Behavior in 2019							
Exposure to conservative media (Dummy)	-0.098	-0.047	0.040	-0.093*	0.093*	0.011	-0.011
	(0.094)	(0.054)	(0.062)	(0.053)	(0.053)	(0.045)	(0.045)
Exposure to liberal media (Dummy)	-0.019	-0.036	0.096	-0.117*	0.117*	0.027	-0.027
	(0.097)	(0.057)	(0.062)	(0.063)	(0.063)	(0.044)	(0.044)

Exposure to farm-related media (Dummy)	-0.040	-0.052	0.074	-0.114**	0.114**	-0.025	0.025
	(0.094)	(0.054)	(0.063)	(0.050)	(0.050)	(0.045)	(0.045)
Number of observations	470	472	472	472	472	472	472

Notes: This table checks the robustness of results in table 5 using the share of different media types as the measurement of media exposure. Column (1) presents marginal effects estimated with probit, while columns (2) – (7) are estimated 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 level at the 10, 5, and 1% level, respectively.