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ARTICLE

Farmers' reactions to the US–China trade war: Perceptions versus behaviors

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Abstract

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

KEYWORDS

media bias, political bias, trade policies, US–China trade war

JEL CLASSIFICATION

D83, F68, F51, Q13, Q17

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1 | INTRODUCTION

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

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

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

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

We collected data from a 2019 mixed-mode survey of 471 crop farmers with over 250 acres of land in operation in Iowa, Illinois, and Minnesota. In per capita terms, the Midwest is one of the regions most affected by trade war tariffs and received the highest MFP payments (Choi & Lim, 2022; Yu et al., 2022). The medium to large farmers we surveyed experience tangible and significant impacts of the US–China trade war, making them ideal for studying reactions to trade policies. In terms of political composition, the three states are neither extremely conservative nor

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liberal, and the rural voters in these states have similar voting records as rural voters nationally.[1] Furthermore, Iowa and Minnesota are battleground states. Iowa is a crucial early-voting state, and farmers in these states have strong political voices (Wilson, 2020). Therefore, our study area and sample have inherent importance.

We report two main findings. First, political bias does affect economic perceptions. Farmers' perceived income loss for the year 2018 decreases by 0.46% when the conservative bias score (average = 4.1 for farmers who consume some conservative media) increases by one, indicating the consumption of more conservative media such as FOX News. When the magnitude of the liberal bias score (average = −3.1 for farmers who consume some liberal media) increases by one, farmers' expected income loss increases by 0.68% ($p < 0.1$). Also, a one-point increase in conservative (liberal) bias score is associated with a 3.4% increase (3.7% decrease) in the probability of farmers perceiving the 2018 MFP payments as helpful. Second, there is little association between media consumption and farming and marketing behavior. Among the five behavior outcomes and 20 coefficients for conservative and liberal media consumption in 2018 and 2019, only liberal media has a marginally significant impact ($p < 0.1$) on pre- and at-harvest marketing in 2018 that does not survive robustness checks.

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

2 | CONCEPTUAL FRAMEWORK

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

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

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

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

3 | DATA AND SUMMARY STATISTICS

3.1 | Survey

Following Dillman et al's. (2014) Tailored Survey Design method, we sent mixed-mode surveys via mail and online through Qualtrics to 3000 crop farmers over the age of 18 with at least 250 acres of cropland in Iowa (44%), Illinois (32%), and Minnesota (23%).[2] The survey asked about farmers' demographics and farm characteristics, most frequently used media sources for trade-war information, perceived farm income loss in 2018 from the trade war before MFP payments, perceived helpfulness of the first round of MFP payments in 2018, and various farming and marketing decisions. We received 722 responses (a 24.1% response rate), and 64% were via mail. After dropping respondents who did not provide expected income loss from the trade war (a main outcome of interest) and other important farm characteristics, 471 usable observations remained. Figure 1 shows the county locations of surveyed farmers' primary farm operations and county-level soybean planted acres in 2018.

3.2 | Key variables

The key independent variable (Supporting Information: Appendix Tables A1 and A2), media bias, comes from the open-ended question, "When seeking information about the trade disruption, what are your three most frequently used media sources?" We classify the reported media outlets into three categories—liberal, neutral, and conservative based on bias scores from Mediabiascheck.com (Supporting Information: Appendix Table A2). The raw bias score for individual sources ranges from liberal bias ($-6 \leq$ bias score ≤ -1) to mostly neutral ($-1 <$ bias score < 1) to right bias ($1 \leq$ bias score ≤ 6). For example, CNN is classified as a liberal media based on a bias score of -2, while Fox News is classified as a conservative media based on a bias score of five. Three farmer associations without available scores (Farm Bureau, Soybean Producers' Association, and Corn Producers' Association) have center-right bias according to the expert opinions of farm management specialists from Iowa State University Extension. Puglisi and Snyder (2015) corroborate these expert opinions. We assign bias scores of two to the three farmer associations and conduct robustness checks by classifying them as neutral. All other farm-related sources are classified as neutral.[3]

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

[3](Two farm related media sources [Supporting Information: Appendix Table 2]) have available bias scores, and both of them are between −1 and 1.

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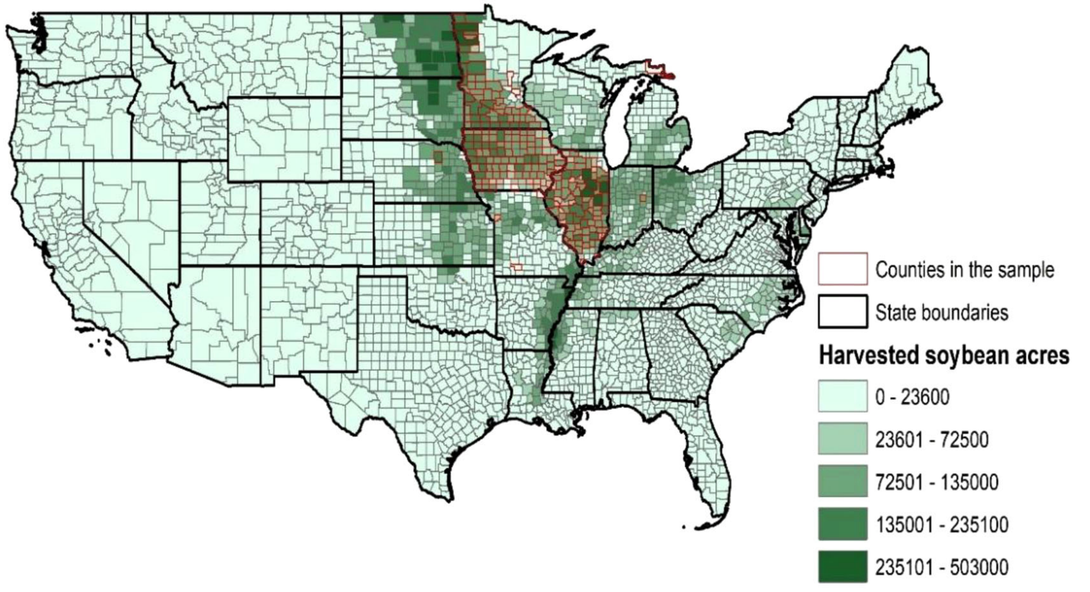

FIGURE 1 Counties in sample and soybean planted acres in 2018. There are 471 farmers in the final analysis. Though most respondents' primary farm operations are in Iowa, Illinois, and Minnesota, several respondents' primary farm operations are located in other states.

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

The first set of outcomes we examine is farmers' perceived income loss from the trade war (before receiving MFP) and the helpfulness of the MFP payments in 2018. The perceived income loss is a categorical variable from 1 (down more than 20%) to 9 (up more than 20%). In the main analysis, we use interval regression (Billard & Diday, 2000) to avoid making assumptions about the mean value for each category. To gauge the accuracy of farmers' perceived income loss, we also estimate actual income loss using two alternative specifications proposed by Janzen and Hendricks (2020) and calculate the gap between actual loss and perceived loss (see Supporting Information: Appendix 4). For this exercise, we convert the categorical variable to the mean of the upper and lower bounds that define each category.[4] The perceived helpfulness of MFP in 2018 is measured on a five-point scale and recoded to a binary variable (0 for "*not at all helpful*" to "*somewhat helpful*"; 1 for "*quite helpful*" and "*very helpful*") for the ease of presentation.

[4]We code scale 1 (*up more than 20%*) as −25%, scale 2 (*up 10%–20%*) as −15%, scale 3 (*up 5%–10%*) as −7.5%, scale 4 (*up less than 5%*) as −2.5%, scale 5 (*no change*) as 0%, scale 6 (*down less than 5%*) as 2.5%, scale 7 (*down 5%–10%*) as 7.5%, scale 8 (*down 10%–20%*) as 15%, and scale 9 (*down more than 20%*) as 25%. We conduct robustness checks with alternative mean value assumptions (Supporting Information: Appendix Table A4).

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

3.3 | Summary statistics

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

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

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

4 | EMPIRICAL METHODS

4.1 | Econometric model

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

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

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

To alleviate the concern of omitted-variable bias, we include a rich set of control variables, Z_{ics}, which include whether the farmer consumes neutral media sources, farmer demographic characteristics, farm characteristics, and others. Demographic variables include farmers' income, age, education, and gender. Farm characteristics include 2018 soybean and corn production (calculated using farmers' 2018 planted acreage and county-level yield), whether the farmer has livestock, whether the farmer has an off-farm job, and the cash rent for that farm. We estimate cash rent by multiplying the county-level cash rent for nonirrigated cropland by the share of rented land. The local political environment is controlled using the share of Republican votes for each county in

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TABLE 1 Summary statistics.

	Mean	SD	Min	Max
Cumulative media bias scores				
Conservative	2.36	2.57	0.00	10.00
Liberal (in absolute value)	0.59	1.33	0.00	9.00
Beliefs				
Expected income loss in 2018 (9: > 20%; 5 = 0%; 1: <−20%)	7.68	1.52	1	9
Expected income loss in 2018 (%)	14.38	9.66	−25	25
MFP helpfulness in 2018 (1 = *Not at all* to 5 = *Very helpful*)	3.61	1.11	1	5
Behaviors				
Soybean storage 2018 (1 = *Decrease a lot* to 5 = *Increase a lot*)	3.39	0.93	1.00	5.00
Share of soybeans planted in 2018	0.47	0.13	0.1	1
Share of corn planted in 2018	0.54	0.13	0.1	1
Share of soybeans sold in nonspot market in 2018	0.46	0.21	0	1
Share of soybeans sold pre- or at-harvest in 2018	0.46	0.29	0	1
Control variables				
Consume neutral media (0 = no; 1 = yes)	0.51	0.50	0.00	1.00
Soybean production in 2018 (Bushel)	29,484	24,933	2,283	266,013
Corn production in 2018 (Bushel)	117,513	109,365	9,192	1,212,993
Share of land rented	0.6	0.28	0	1
Nonirrigated land cash rent per acre ($ per acre)	210.4	42.84	42	289
Age	60.52	10.53	27	85
Attend some college or above (0 = no; 1 = yes)	0.36	0.48	0	1
Male (0 = no; 1 = yes)	0.97	0.17	0	1
Willingness to take risks (1–7)	4.47	1.27	1	7
Have livestock on farm (0 = no; 1 = yes)	0.38	0.49	0	1
Have off-farm job (0 = no; 1 = yes)	0.69	0.46	0	1
Farm income ($)	657,383	482,649	30,000	1,500,000
Ineligible for MFP (Income above $900,000)	0.21	0.40	0	1
Surveyed after 05/2019 (0 = no; 1 = yes)	0.61	0.10	0	1
County Republican vote share	656,147	482,881	30,000	1,500,000

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

the 2016 presidential election. We also control for whether the farmer is eligible for the first round of MFP payments, measured by whether the farmer has an income below $900,000 (USDA, 2018). The model includes congressional district fixed effects, FE_d, to capture time-invariant differences across locations. Due to the limitation of sample size, including fixed effects at finer geographical

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levels will absorb most of the variation. The error term (ε_{icd}) is clustered at the county level to allow for error correlation between observations within a county.

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

5 | RESULTS

5.1 | Perceived economic conditions

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

The main results in Table 2 are how the consumption of partisan media is associated with farmers' perceived income loss and the helpfulness of MFP payments. In Column (1), interval regression results show that a one-point increase in the conservative bias score leads to 0.46% lower expected income loss. For liberal media consumption, Column (1) shows that a one-point increase in liberal media bias score is associated with a 0.68% increase in perceived income loss. Back-of-the-envelope calculations show that the average consumer of conservative (liberal) media perceives income loss to be 1.9% (2.1%) percentage points lower (higher), compared to the average perceived income loss of 14.4%.[6] The implied difference in perceived income loss between the average consumers of conservative and liberal media sources (with and without consuming neutral media) is 4.0% of the total income, which is equivalent to about \$26,000 for the average farm with an income of \$657,147 (Table 1). The results on the gap between actual and perceived income loss (Table 2, Columns 2 and 3) show that conservative bias changes the difference in the positive direction, consistent with conservative bias lowering expected income loss. The calculation of the actual-perceived income gaps involves assumptions on the mean values of income intervals reported in the survey. Robustness checks using alternative mean value assumptions for income loss intervals show similar qualitative results with some changes in effect size (Supporting Information: Appendix Table A4).

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

[5]See Supporting Information: Appendix Figures A1 and A2 for a more detailed illustration of these results using Lowess graphs.

[6]These numbers are estimated by multiplying the regression coefficient for conservative (liberal) bias by the average bias score faced by consumers of conservative (liberal) farmers (Supporting Information: Appendix Table A1).

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TABLE 2 Media consumption and farmers' perceived income loss, the gaps between perceived and actual income loss, and perceived MFP payment helpfulness.

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

(Continues)

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TABLE 2 (Continued)

	Income loss (1)	Gap method 1 (2)	Gap method 2 (3)	MFP helpfulness (4)
Congressional Dist. FE	Yes	Yes	Yes	Yes
N	471	471	471	461

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

5.2 | Media and behavior

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

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

5.3 | Additional robustness checks

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

Second, we attempt to address the concern that biased media consumption may be an inaccurate proxy for partisan alignment. We argue that if a farmer consumes only conservative or liberal media

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TABLE 3 Media consumption and farmers' behavior.

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

(Continues)

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TABLE 3 (Continued)

	Soybean storage (1)	Share of soybeans planted (2)	Share of corn planted (3)	Soybeans sold pre- and at-harvest (4)	Soybean sold on nonspot markets (6)
Congressional district FE	Yes	Yes	Yes	Yes	Yes
N	414	471	471	471	471

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

[a]Coefficient dropped because of perfect collinearity.

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

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

6 | DISCUSSION AND CONCLUSIONS

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

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

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

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TABLE 4 Robustness checks.

	Income loss (1)	Gap method 2 (2)	MFP helpfulness (3)	Storage (4)	Share planted (5)	Sold pre- and at-harvest (6)	Sold on nonspot markets (7)
Panel A: Media bias measure: Dummy							
Conservative	−1.419	−1.782	0.158***	−0.015	0.005	−0.010	−0.022
	(1.109)	(1.350)	(0.046)	(0.026)	(0.008)	(0.030)	(0.019)
Liberal	3.232**	3.141*	−0.110*	0.036	0.002	0.029	0.027
	(1.384)	(1.751)	(0.057)	(0.029)	(0.013)	(0.035)	(0.028)
Panel B: Media bias measure: Share							
Conservative	−0.946	−1.793	0.195***	−0.022	0.010	−0.003	0.012
	(1.626)	(2.093)	(0.069)	(0.036)	(0.009)	(0.043)	(0.028)
Liberal	5.110**	5.046*	−0.134	0.045	0.016	0.042	0.063
	(2.268)	(2.729)	(0.096)	(0.045)	(0.024)	(0.059)	(0.045)
Panel C: Media bias measure: Farm-related as neutral							
Conservative	−0.459**	−0.475*	0.032***	−0.005	0.001	0.008	−0.003
	(0.221)	(0.278)	(0.009)	(0.005)	(0.002)	(0.005)	(0.003)
Liberal	0.658	0.893*	−0.036**	0.006	0.001	0.016	0.008
	(0.408)	(0.469)	(0.017)	(0.008)	(0.004)	(0.010)	(0.008)
Panel D: Drop observation with both conservative and liberal media consumption							
Conservative	−0.470**	−0.542**	0.037***	−0.007	0.001	0.002	−0.006
	(0.219)	(0.268)	(0.009)	(0.005)	(0.002)	(0.006)	(0.004)
Liberal	0.798	0.792	−0.029	−0.010	0.003	0.015	0.008
	(0.543)	(0.651)	(0.022)	(0.010)	(0.006)	(0.013)	(0.010)
Panel E: Using weighted regression to correct for conservative/liberal imbalance							
Conservative	−0.468**	−0.488*	0.034***	−0.002	0.001	0.005	−0.004
	(0.223)	(0.257)	(0.009)	(0.005)	(0.002)	(0.005)	(0.003)
Liberal	0.680	0.870*	−0.035**	0.000	0.001	0.017*	0.009
	(0.438)	(0.464)	(0.016)	(0.008)	(0.003)	(0.010)	(0.008)

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

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

In contrast to the strong correlation between media consumption and farmers' perceptions, we find little correlation between partisan media consumption and economic decisions. Though we

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cannot completely rule out partisan biases in behaviors, the absence of statistically significant effects in almost all behaviors studied suggests that political alignments have weak effects, if any, on economic behaviors. The inconsistency between stated perceptions and behavior here adds weight to the argument that survey responses about economic perceptions are subject to cheerleading.

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

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DATA AVAILABILITY STATEMENT

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

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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. https://doi.org/10.1257/jel.51.2.423

Autor, David, David Dorn, Gordon Hanson, and Kaveh Majlesi. 2020. "Importing Political Polarization? The Electoral Consequences of Rising Trade Exposure." *American Economic Review* 110(10): 3139–83. https://doi.org/10.1257/aer.20170011

Balistreri, Edward, Wendong Zhang, and John Beghin. 2020. "The State-level Burden of the Trade War: Interactions between the Market Facilitation Program and Tariffs." In *Agricultural Policy Review* (pp. 1–10). Ames, IA: Center for Agricultural and Rural Development (CARD), Iowa State University.

Billard, Lynne, and Edwin Diday. 2000. "Regression Analysis for Interval-valued Data." In *Data Analysis, Classification, and Related Methods* (pp. 369–74). Berlin: Springer.

Blonigen, Bruce A. 2011. "Revisiting the Evidence on Trade Policy Preferences." *Journal of International Economics* 85(1): 129–35. https://doi.org/10.1016/j.jinteco.2011.05.010

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

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Bullock, John G., and Gabriel Lenz. 2019. "Partisan Bias in Surveys." *Annual Review of Political Science* 22: 325–42. https://doi.org/10.1146/annurev-polisci-051117-050904

Bunge, Jacob. 2020 "Farmers Stick With Trump, Despite Trade-War Pain." The Wall Street Journal. 2020.

Che, Yi, Yi Lu, Justin R. Pierce, Peter K. Schott, and Zhigang Tao. 2022. "Did Trade Liberalization With China Influence US Elections?" *Journal of International Economics* 139: 103652. https://doi.org/10.1016/j.jinteco.2022.103652

Choi, Jung-Sup, and Peter G. Helmberger. 1993. "Acreage Response, Expected Price Functions, and Endogenous Price Expectations." *Journal of Agricultural and Resource Economics* 18(1): 37–46. https://onlinelibrary.wiley.com/toc/14678276/0/0

Choi, Jaerim, and Sunghun Lim. 2022. "Tariffs, Agricultural Subsidies, and the 2020 US Presidential Election." *American Journal of Agricultural Economics*. https://doi.org/10.1111/ajae.12351

Dillman, Don A., Jolene D. Smyth, and Leah M. Christian. 2014. *Internet, Phone, Mail, and Mixed-mode Surveys: The Tailored Design Method*. New Jersey: John Wiley & Sons.

Evans, Geoffrey, and Mark Pickup. 2010. "Reversing the Causal Arrow: The Political Conditioning of Economic Perceptions in the 2000–2004 US Presidential Election Cycle." *The Journal of Politics* 72(4): 1236–51. https://doi.org/10.1017/S0022381610000654

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. https://doi.org/10.1093/qje/qjz036

Fetzer, Thiemo, and Carlo Schwarz. 2021. "Tariffs and Politics: Evidence From Trump's Trade Wars." *The Economic Journal* 131(636): 1717–41. https://doi.org/10.1093/ej/ueaa122

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. https://doi.org/10.1017/S0003055409990098

Gerber, Alan S., and Gregory A. Huber. 2010. "Partisanship, Political Control, and Economic Assessments." *American Journal of Political Science* 54(1): 153–73. https://doi.org/10.1111/j.1540-5907.2009.00424.x

Grant, Jason H., Shawn Arita, Charlotte Emlinger, Robert Johansson, and Chaoping Xie. 2021. "Agricultural Exports and Retaliatory Trade Actions: An Empirical Assessment of the 2018/2019 Trade Conflict." *Applied Economic Perspectives and Policy* 43(2): 619–40. https://doi.org/10.1002/aepp.13138

Janzen, Joseph P., and Nathan P. Hendricks. 2020. "Are Farmers Made Whole by Trade Aid?" *Applied Economic Perspectives and Policy* 42(2): 205–26. https://doi.org/10.1002/aepp.13045

Janzen, Joseph P., Trey Malone, K. Aleks Schaefer, and Daniel P. Scheitrum. 2021. "Political Returns to Ad Hoc Farm Payments." *Applied Economic Perspectives and Policy* 45(1): 555–78.

Jerit, Jennifer, and Barabas Jason. 2012. "Partisan Perceptual Bias and the Information Environment." *The Journal of Politics* 74(3): 672–84. https://doi.org/10.1017/s0022381612000187

Jerit, Jennifer, and Yangzi Zhao. 2020. "Political Misinformation." *Annual Review of Political Science* 23: 77–94. https://doi.org/10.1146/annurev-polisci-050718-032814

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): 435–54. https://doi.org/10.1111/agec.12427.

Kunda, Ziva. 1990. "The Case for Motivated Reasoning." *Psychological Bulletin* 108(3): 480–98. https://doi.org/10.1037/0033-2909.108.3.480

Levy, Ro'ee. 2021. "Social Media, News Consumption, and Polarization: Evidence From a Field Experiment." *American Economic Review* 111(3): 831–70. https://doi.org/10.1257/aer.20191777

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. https://doi.org/10.1016/j.asieco.2020.101216

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

McGrath, Mary C. 2017. "Economic Behavior and the Partisan Perceptual Screen." *Quarterly Journal of Political Science* 11(4): 363–83. https://doi.org/10.1561/100.00015100

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

Prior, Markus. 2013. "Media and Political Polarization." *Annual Review of Political Science* 16: 101–27. https://doi.org/10.1146/annurev-polisci-100711-135242

Puglisi, Riccardo, and James M. Snyder. 2015. "The Balanced US Press." *Journal of the European Economic Association* 13(2): 240–64. https://doi.org/10.1111/jeea.12101

Strömbäck, Jesper, Michael Karlsson, and David Nicolas Hopmann. 2012. "Determinants of News Content: Comparing Journalists' Perceptions of the Normative and Actual Impact of Different Event Properties When Deciding What's News." *Journalism Studies* 13(5–6): 718–28.

USDA. 2018. *Market Facilitation Program (MFP) Fact Sheet*. https://www.fsa.usda.gov/Assets/USDA-FSA-Public/usdafiles/FactSheets/2018/Market_Facilitation_Program_Fact_Sheet_September_2018C.pdf

USDA. 2019. Ag Census 2017, Volume 1, Chapter 2, 350pp. https://www.nass.usda.gov/Publications/AgCensus/2017/Full_Report/Volume_1,_Chapter_2_US_State_Level/st99_2_0008_0008.pdf

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Viskupič, Filip, Evren Celik Wiltse, and David L. Wiltse. 2022. "Pocketbook Versus Identity? Farmers' Attitudes Towards International Trade." *The Social Science Journal* 1–11 https://doi.org/10.1080/03623319.2022.2082176

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

Yu, Jisang, Nelson B. Villoria, and Nathan P. Hendricks. 2022. "The Incidence of Foreign Market Tariffs on Farmland Rental Rates." *Food Policy* 112: 102343. https://doi.org/10.1016/j.foodpol.2022.102343

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