# Retaliatory Tariff and 2018 Mid Term Election: Was there an effect of Chinese soybeans Tariff ?

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**Abstract**

The 2018 Congressional election was held when U.S. and China involved in a trade war. The U.S. protectionist tariffs were retaliated by China with tariff on U.S. agricultural exports in which share of soybeans was substantial. I investigate the effect of Chinese soybeans tariff on the Republican vote share change between 2016 and 2018. Using county level election data and per worker tariff exposure variable I find significantly negative and spatially heterogeneous association between soybeans tariff and Republican vote share change. Specially I find that tariff effect is more prominent in counties where Donald Trump's vote share was between 40%-50% in 2016. Further, I find a significant and relatively large negative association between Chinese soybean tariff and Republican vote share change in counties which ship soybeans through Pacific Northwest ports. The estimates are stable across models which are controlled for per worker U.S. trade protection and overall real wage effect of 2018 trade war.

***Keywords***— Trade war 2018, Soybean tariff, trade policy, electoral competition

## 1 Introduction

The 2018 mid-term election in the U.S. was held under a challenging trade policy environment. A U.S. county was subjected to four different forces pertinent to trade. They were, localized adjustment costs caused by import competition, tariff protection on manufacturing sector given by Donald Trump, retaliatory tariff imposed by U.S. trade partners including China, and farm subsidy under Market Facilitate Program (MFP). The later three forces were direct outcomes of 2018 trade war (Blanchard, Bown, and Chor, 2019; Fajgelbaum et al., 2020). In 2018, Trump administration increased tariff on U.S. imports from key trade partners including China prompting a wave of retaliatory tariffs on U.S. agricultural exports. The tariff raise on agricultural products by China heavily contributed the overall tariff burden resulted by 2018 trade war. China, the main buyer of the U.S. soybeans increased soybeans tariff by 25%, inflicting damage on U.S. soybeans export, negatively affecting U.S. soybeans price, and influencing domestic planting decisions (Grant et al., 2019; Hitchner, Menzie, and Meyer, 2019). Economic analyses as well as anecdotes pointed to a possible political motive behind the structure of retaliatory tariff schedule, intended to inflict harm Republicans electorally (Fetzer and Schwarz, 2019). The retaliatory tariff burden was heavily on the Republican leaned counties (Fajgelbaum et al., 2020). Further U.S. government provided farm subsidies including $1.65 per bushel of soybeans produced by the U.S. farmers to mitigate the repercussions (Blanchard, Bown, and Chor, 2019). Given this background, I ask whether the soybeans tariff imposed by China affected the vote share of the Republicans in 2018 congressional election. Further, I asked whether the MFP subsidy was helpful to mitigate the impact of retaliatory tariff on the Republican vote share . I test whether the Chinese soybeans tariff effect is disproportionately higher in counties which ship soybeans through Pacific Northwest (PNW) ports. Further I test whether the Chinese soybeans tariff is effective in reducing Republican vote share in closely competed counties in 2016 presidential election.

Soybeans export is the major agricultural commodity export from U.S. to China. As shown in figure (1) export value of U.S. soybeans to China in 2017, just before the trade war 2018, was $12 billion. Moreover, China bought 57% of total U.S. soybeans export to the world. Only three commodities which are among the top ten U.S. agricultural exports to China, i.e. soybeans (HS 1201), hides and skins (HS 4101), and sorghum (HS 1007) depend on Chinese market for more than 50% exports(Figure (1)). Based on the export value and the dependence on Chinese market, I identify soybeans, sorghum, and cotton as key crops exported to China by U.S. I include cotton (HS 5201) to this list of key crops, as the annual export value exceeded $500 million. An important feature of the export market for soybeans and sorghum is that, export market is heavily concentrated as implied by high concentration ratio and Herfindhal-Hirschman index (HHI) (Table 1). Export market for U.S. cotton is less concentrated compared to soybeans and sorghum. Further it does not rely heavily on China.

Given that more than half of U.S. soybeans exceeding $12 billion went to China, soybeans tariff was a key retaliatory tariff measure taken by China. By the time of 2018 mid-term election China had announced and implemented tariffs on key agricultural exports from U.S. to China. Table (2) shows tariff rates announced for key agricultural exports [1] from U.S. to China. China imposed tariff on U.S. exports in several waves. The reported tariffs are as of September 2018. Chinese retaliation in response to U.S. section 301 tariffs in July 2018, imposed 25% tariff on U.S. soybeans. Retaliatory tariffs on cotton, sorghum, dairy products, and hides and skins were also effective from July, 2018 (Regmi, 2019; USDA, 2019a).

Chinese soybeans tariff imposed in July, 2018 immediately affected soybeans market year 2018-2019. Soybeans market year for 2018/2019 expands from August 2018 to September 2019[2]. Compared to 2017-2018 market year, soybeans export to China fell by 74.5% from $12232 million to $3119 million. U.S. sorghum exports to China fell by 37% from $839 million to $521 million (Figure 2). However U.S cotton exports to China fell just by 5% [3]. Trade data show that U.S. soybeans export to world fell by 20%. It implies, although part of the loss from Chinese retaliation was compensated by trade deflection, overall U.S. soybeans export suffered significant losses in 2018-2019 market year. Carter and Steinbach (2020) estimate that trade destruction effect of retaliatory tariff on U.S. soybeans export is $7.1 billion. The trade deflection to other countries is estimated to be just $113 million[4].

[1]For each commodity U.S. export value exceeded $500 million in 2017

[2]Anticipation of trade war started to affect soybeans prices from April 2018 when US announced $50 billion tariff on Chinese imports. Soybeans futures prices fell rapidly beginning from May, 2018 (USDA, 2019c)

[3]Among other top ten U.S. exports, wheat exports fell 70%. U.S nuts exported to China grew by 9%. Pork exports fell just by 16%. However all of these commodities' exported to China value less than $500 million in 2017 .

[4]Carter and Steinbach (2020) finds that trade diversion, the increased import from non-retaliatory countries, for soybeans is $3.7 billion.They find that South American countries primarily benefits from the retaliatory tariff increases. picking up a large share of the excess demand for soybeans.

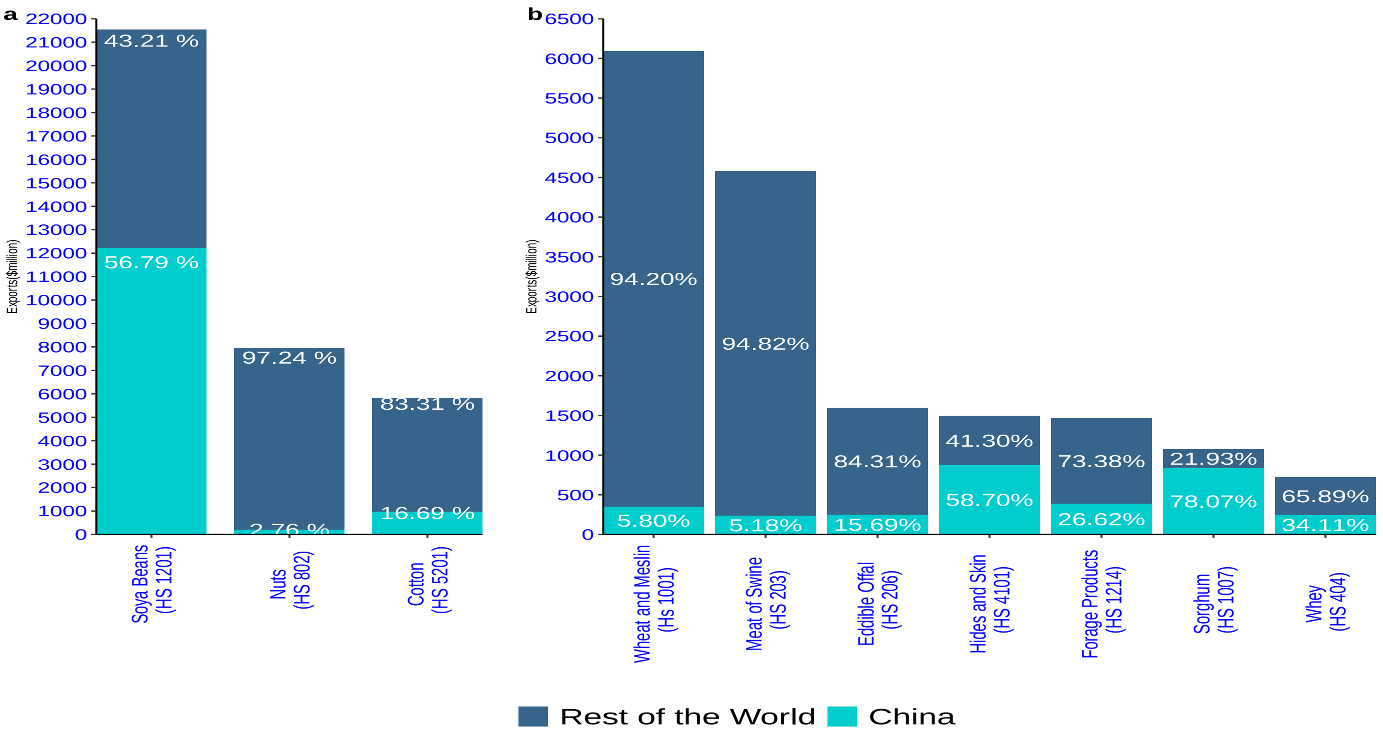


Figure 1: Top ten agricultural exports from U.S. to China at HS-4 in 2017

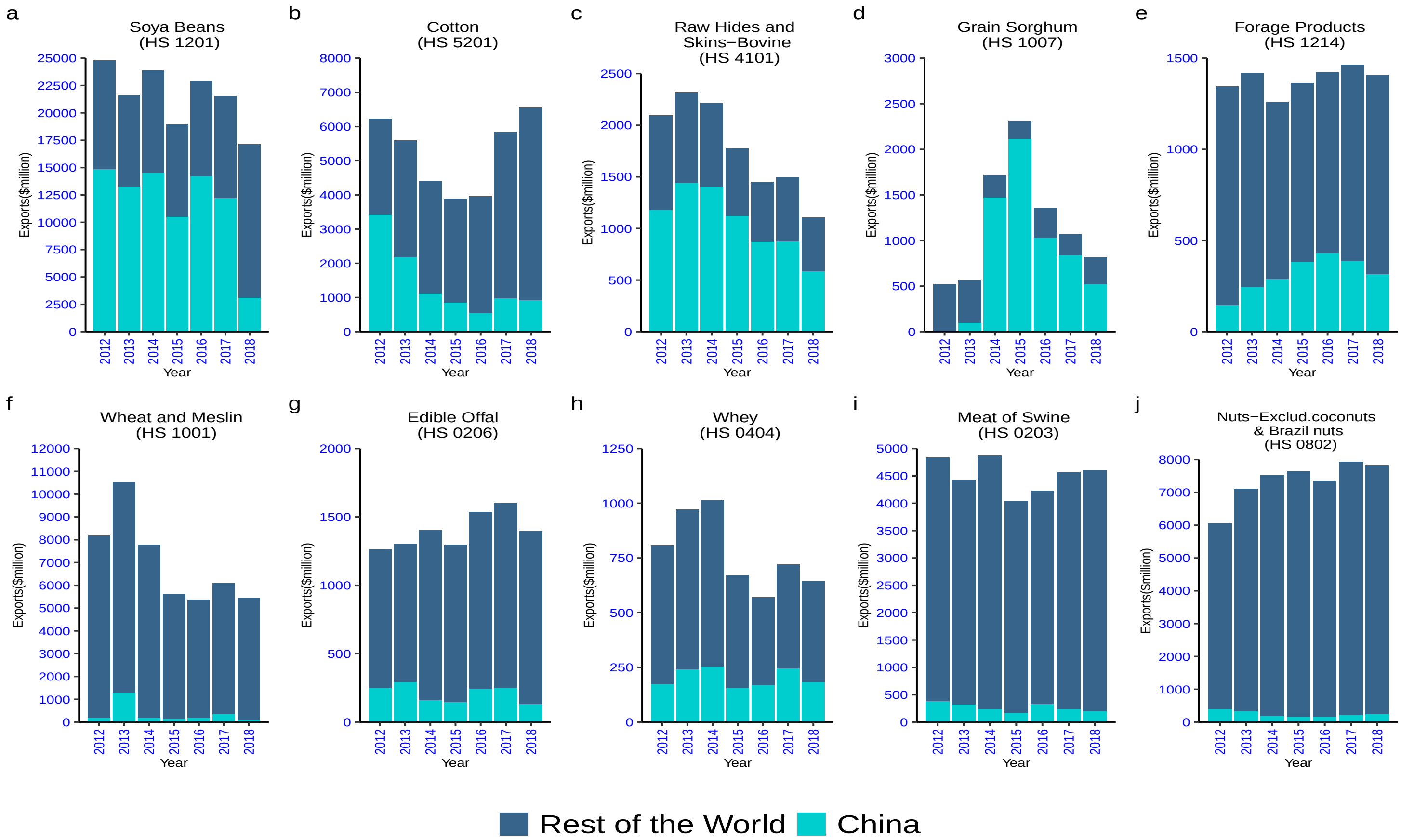


Figure 2: Annual top ten U.S. exports to China from 2012 to 2018

Table 1: Export-destination wise market concentration of key U.S. exports to China

| Commodity | HS code | Share of Export to China | Concentration Ratio [1] (Top 3 buyers) | Herfindahl–Hirschman Index(HHI)[2] |
|---|---|---|---|---|
| Soybeans | 1201 | 56.790 | 65.862 (1) | 3367 |
| Sorghum | 1007 | 78.065 | 88.327 (1) | 6206 |
| Cotton | 5201 | 16.688 | 47.343 (2) | 1036 |

[1] Concentration ratio; $CR_3 = \sum_{i=1}^{3} S_i$, where $S_i$ is the market share of each top three buyer. In parentheses China's rank among top three buyers is given. $CR_3$ measures the concentration of U.S. export markets.
[2] Herfindahl–Hirschman Index (HHI) i; $HHI = \sum_i S_i^2$: where $S_i$ is market share of each buyer.The HHI takes into account the relative size distribution of the buying countries . It approaches zero when market share is distributed among large number of buyers and 10,000 if one country buys all exported quantity.
*Source:* Author's calculations using International Trade Center (ITC) Trade Map data.

Table 2: Chinese Retaliatory Tariff on U.S. Agricultural Exports

| Commodity | HS code | MFN Tariff(%) | $\Delta$Tariff (%) as of Sept 2018 [1] |
|---|---|---|---|
| Soybeans | 12019010 and 12019020 | 3 | 25 |
| Pork [2] | 02031110 | 20 | 25 |
| | 02031190 | 20 | 25 |
| | 02031200 | 20 | 50 |
| | 02031900 | 20 | 50 |
| | 02032110 | 12 | 25 |
| | 02032190 | 12 | 50 |
| | 02032200 | 12 | 50 |
| | 02032900 | 12 | 50 |
| | 02042200 | 15 | 25 |
| | 02062900 | 12 | 25 |
| | 02063000 | 20 | 25 |
| | 02064100 | 20 | 50 |
| | 02064900 | 12 | 50 |
| | 16024100 | 5 | 25 |
| Cotton | 52010000 | 1 (in quota), 40 (over-quota) | 25 (in quota), 25 (over-quota) |
| Sorghum | 10079000 | 2 | 25 |
| Dairy [3] | Chapter 4 HS lines (except honey) | Range 2-20 | 25 |
| Hides and Skins | 4101,4102, and 4103 | Range 5-9 | Range 10-17 |

[1] Tariff effective dates vary by commodity. Pork tariffs were enforced from 2 April 2018. Chinese retaliation in response to U.S. section 301 tariffs in July 2018, included soybeans.
[2] USDA defines pork including HS codes 020311, 020312, 020319, 020321, 020322, 020329, 021011, 021012, 021019, 160241, 160242, and 160249
[3] Dairy products include many tariff lines and tariff rates vary accordingly.
*Source* (Regmi, 2019; USDA, 2019a)

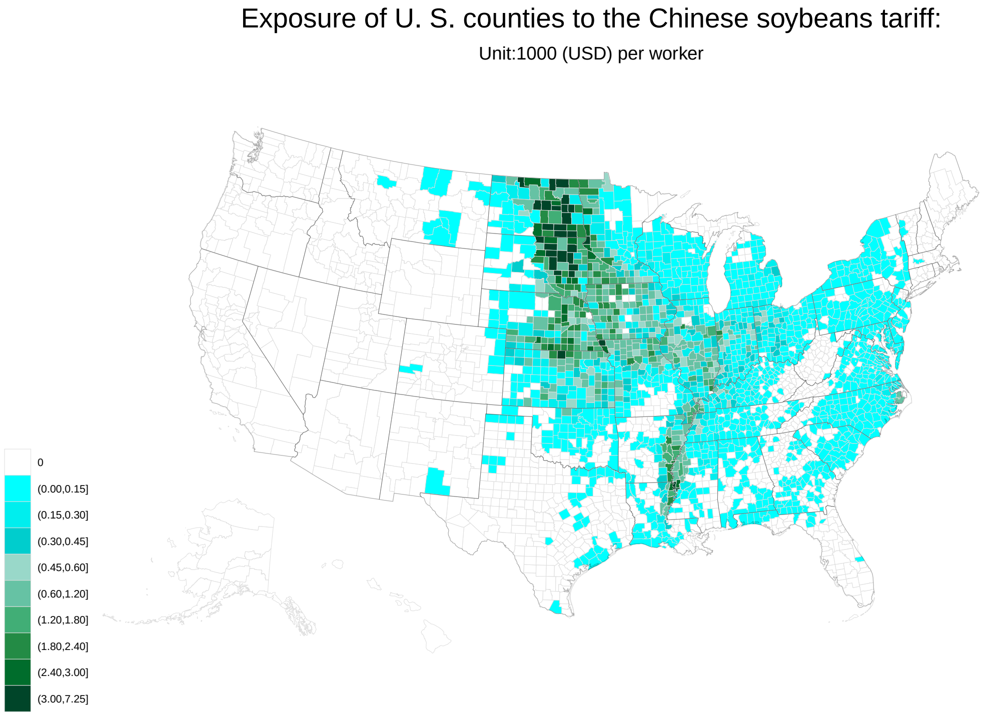


Figure 3: Distribution of the Chinese soybeans tariff incidence across U.S counties

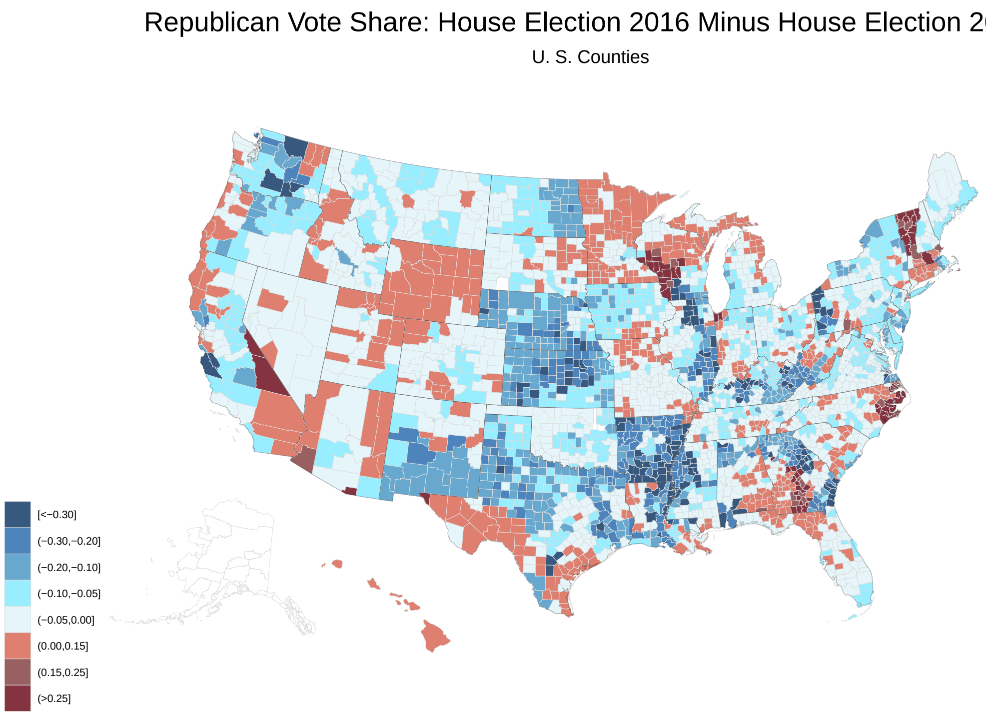


Figure 4: Republican vote share change , 2016 House election minus 2012 House election, across U.S counties

Anecdotally, exerting a political pressure on Trump as a target of retaliatory tariff is widely acknowledged, mainly due to targeting commodities like soybeans. Chinese soybeans import market is heavily concentrated on Brazil and U.S. soybeans. In 2017, 88% of Chinese soybeans was from Brazil and U.S. while U.S. share was 33%. If we assume China imports soybeans based on comparative advantage rationale of free trade, tariff retaliation on one of China's major soybeans supplier, is economically harmful to China too. This fact gives first indication that targeting soybeans in 2018 trade war has a political motivation given that soybeans are grown by Republican leaned counties. Parametric and non-parametric analyses also point to the fact that county level retaliatory tariff effect increases with county level Republican vote share in 2016 election[5] (Fetzer and Schwarz, 2019; Fajgelbaum et al., 2020).

The retaliation effect on U.S. soybeans sector varied across the U.S. regions implying geographically concentrated consequent electoral effects. There are four major soybeans surplus regions. They are Upper Mississippi, OIMK (or Ohio, Indiana, Michigan, Kentucky), Northern Plains and Central Plains. The states in Northern Plains and Central Plains regions export their soybeans through PNW ports while the Upper Mississippi and OIMK regions primarily use the river to export and rail to domestic soybean deficit regions in the Southeast[6] (Economics, 2012) (Table A1). The PNW ports are geographically close to China . Disproportionate effect felt by states that exported soybeans to China through PNW ports were visible from the increased soybeans stocks and weakened soybeans prices in these states compared to soybeans producing states that export to markets other than China through Gulf ports (Hitchner, Menzie, and Meyer, 2019). Table A2 shows that Minnesota, Nebraska, North Dakota, South Dakota, and Wisconsin transport soybeans predominantly to PNW on railroad. Less than 20% of soybeans transported on rail in Illinois and Indiana are exported through PNW. In this study I take states in Northern plains and Central plains as states that ship soybeans via PNW.

In summer 2018, U.S. government announced farm subsidies under MFP. The trade assistance package totalling \$12 billion had \$9.4 billion for direct payment to producers. As soybeans sector was the sector hit hardest by trade war, around \$7 billion was disbursed to soybeans producers as direct payment as calculated by the American Farm Bureau Federation (AFBF) (AFBF, 2019). MFP subsidies covered key export commodities like cotton, hogs, dairy,sorghum, and wheat (USDA, 2018). The 2018 Congressional election was held under the agricultural trade events described above.

The 2018 Congressional election in U.S. provides us an opportunity to investigate whether the political objective of Chinese retaliatory tariff achieves an electoral effect. In this research I ask, what is the direction and magnitude of the association of Chinese soybeans tariff on the difference between 2016 and 2018 Republican vote share in U.S. Congressional elections. Further I ask whether the MFP payments could mediate the effect of Chinese retaliatory tariff effect. Finally I ask whether the retaliatory tariff effect is higher in counties which shipped soybeans via PNW in the U.S. Further I test the hypothesis that, electoral effect of retaliatory tariff may disproportionately larger in counties which were closely competed in 2016. Such counties have voters who are likely to be closer to an indifferent point between Republican party and Democratic party.

The electoral effect of 2018 trade war is investigated in several papers in the economic and political science literature. Blanchard, Bown, and Chor (2019) find that Republican candidates

[5] Fetzer and Schwarz (2019) shows that China put a large weight on maximizing political targeting.
[6] Alabama, Florida, Georgia, North Carolina, South Carolina, and Tennessee

lost support in the 2018 congressional election in counties more exposed to trade retaliation and the adverse effect is partially mitigated by the US agricultural subsidies announced in summer 2018. Further empirical studies point to the fact that electoral losses for Republican party are driven by agricultural tariffs (Blanchard, Bown, and Chor, 2019; Chyzh and Urbatsch, 2019). Chyzh and Urbatsch (2019) investigate the effect of Chinese soybeans tariff on Republican's vote share in 2018. Given these papers in the literature, I contribute to the strand of literature on electoral effect of 2018 trade war, by investigating the mitigating effect of soybeans MFP subsidy and investigating the spatially heterogeneous effect on counties which ship soybeans from PNW ports. Further I estimate the differential effect of soybeans tariff across the counties divided to competitive bins based on the degree of electoral competition between Republican and Democratic parties in 2016 presidential election. I control for the overall real wage effects of 2018 tariff war to better measure the additional effect of Chinese soybeans tariff.

## 2 Literature Review

The 2018 trade war had negative impact on U.S. economy. Amiti, Redding, and Weinstein (2019) estimated that the deadweight loss due of U.S. tariffs in 2018 was to be around \$8.2 billion with an additional cost of \$14 billion to U.S. consumers and importers. These estimates are in line with Fajgelbaum et al. (2020). Further the US import tariffs were completely passed into US domestic prices and prices of US-made intermediate and final goods rose significantly in sectors affected by the tariffs relative to unaffected sectors (Cavallo et al., 2019; Amiti, Redding, and Weinstein, 2019). The trade destruction effect of 2018 trade war on U.S. agricultural export was substantial. The losses in foreign trade with retaliatory countries exceed the gains from trade deflection to non-retaliatory countries by more than \$14.4 billion. The trade destruction effects were highest for soybeans, pork products, and coarse grains. (Carter and Steinbach, 2020).

Generally, a tariff increase on imported goods can be explained by national income rationale due to the importance of tariffs as a source of revenue Hansen (1990). Governments can maximize national income by raising tariffs on goods with more inelastic foreign export supply (Johnson, 1953; Broda, Limao, and Weinstein, 2008). However such national income rationale should be detected by the variation of tariff levels across sectors. In 2018, around 99.8% varieties[7] were hit with either 10% or 25%. Similar pattern exists in the retaliatory tariff schedules Fajgelbaum et al. (2020). The largely monotonic tariff schedules suggest that 2018 tariff increase was not driven by sector specific interests groups as in "protection for sale" strand of literature (Grossman and Helpman, 1994; Goldberg and Maggi, 1999; Gawande and Bandyopadhyay, 2000).

Though, there is no evidence for national income or special interest group influence behind 2018 tariff increase by U.S. Fajgelbaum et al. (2020) show that import protection is biased towards products made in electorally competitive counties in 2016 presidential election. Such tariff structure is explained by electoral competition in which trade policy favors the voters who are closer to be indifferent between candidates (Grossman and Helpman, 2005; Evans, 2009). An electoral rationale can be seen in Chinese retaliatory tariff schedule as retaliations disproportionately targeted agricultural sectors which are mostly concentrated in Republican leaned counties as measured in 2016 presidential election results (Fetzer and Schwarz, 2019; Fajgelbaum et al., 2020).

[7] Defined as country-product pairs. A product is defined as 10-digit HS product code

In the literature on interaction between trade policy and voting behavior, Heckscher–Ohlin (HO) model and the Ricardo–Viner (RV) model are used to characterize the trade policy preferences (Scheve and Slaughter, 2001). RV model assumes that factors are immobile across sectors and the income of specific factors are linked to their sector of employment. Trade policy changes induce changes in relative product prices and redistribute income across sectors. Comparatively disadvantaged sectors, which face price declines realize income losses. Comparatively advantaged sectors, which face prices increase realize income gains. Likewise the trade policy preferences are determined by the sector of employment of voters. Model based analyses show that all U.S. counties faced real wage decline as a result of the 2018 trade war (Fajgelbaum et al., 2020). Further as discussed in the introduction, sectors like soybeans were disproportionately affected. The trade destruction effect also was prominent for soybeans. Given this background we can expect that trade policy preference of the voters' in U.S counties was influenced by the tariff war in 2018.

A growing body of literature has focused on the electoral effect of 2018 tariff war on 2018 U.S. Congressional election (Blanchard, Bown, and Chor, 2019; Fetzer and Schwarz, 2019; Chyzh and Urbatsch, 2019). Using a tariff shock measure and retaliatory tariff shock measure[8], (Blanchard, Bown, and Chor, 2019) report a negative and significant effect of retaliatory tariff on Republican vote share change from 2016 to 2018. Importantly, they report that the electoral losses are partially mitigated by the US agricultural subsidies under MFP.They do not find significant electoral gains from U.S. tariff protection and electoral losses were driven by retaliatory tariffs on agricultural products. (Blanchard, Bown, and Chor, 2019) capture the trade protection effect of 2018 trade war incorporating a tariff shock measure accounting for the trade protection given by Trump for certain sectors[9]. However trade war affected real wages in counties via input-output linkages. (Fajgelbaum et al., 2020) report that all counties experienced reductions in tradeable real wages based on model based counterfactuals.

Closely related to the current paper, Chyzh and Urbatsch (2019) test whether counties highly reliant on soybeans production saw decreased support for the Republican Party and report a robust inverse relationship between county-level soybeans production and the change in Republican vote share between the 2016 and 2018 congressional elections. Chyzh and Urbatsch (2019) measure county's economic reliance on soybeans using soybeans production in millions of bushels and in dollar sales.

# 3 Empirical Model

I estimate the following empirical model.

$$\begin{aligned}\Delta Outcome_c^{16,18} &= \alpha + \beta_1 TS_c^{US,China} + \beta_2 MFPSubsidy_c \\ &+ \beta_3 TS_c^{US,China} \times MFPSubsidy_c + \beta_4 \Delta RealWage + \gamma \mathbf{X}_c \\ &+ D_s + \epsilon_c\end{aligned} \tag{1}$$

The dependent variable $\Delta Outcome_c^{16,18}$ is the Republican vote share change between 2016 and 2018 congressional elections. $TS_c^{US,m}$ is the Chinese soybeans retaliatory tariff shock faced by U.S. counties. I constructed Chinese retaliatory tariff shock as per the equation given below.

[8] The retaliatory tariff shock comprises the tariff responses by the US' four largest trading partners, Canada, Mexico, China, and the EU (Blanchard, Bown, and Chor, 2019).

[9] Trade protection measure incorporates U.S. tariffs on washers and solar panels (Section 201), steel and aluminum (Section 232), and July-August 2018 round of tariffs on \$50 billion of U.S. imports from China, and additional \$200 billion in September 2018 (Section 301)

$$TS_c^{US,China} = \frac{M_c \Delta\tau_{soybeans}^{US,China}}{L_c} \tag{2}$$

where $M_c$ is the county level soybeans sales recorded in 2017, $\Delta\tau_{soybeans}^{US,China}$ is the tariff increased by China as a retaliation, and $L_c$ is the county labor force in 2016. $MFPSubsidy_c$ is the subsidy disbursed to a county under MFP subsidy program. The MFP subsidy per worker is calculated similarly by multiplying the county-level soybean production by \$1.65[10]. However, due to multicollinearity it was substituted by the per worker total MFP crop subsidy measure. $\Delta RealWage$ is the change of real wage due to trade war, in tradeable sectors as a percentage. The model is controlled for a broad set of economic and demographic characteristics which can be taken as the determinants of voting behavior following the literature. Key control variables in vector $\mathbf{X}_c$ are the share of the population with health insurance prior to the 2018 elections, and the change in the share with health insurance in the years since the Affordable Care Act was enacted in 2010. Healthcare was a key electoral issue in 2018.

I include population shares by age cohorts, gender, and race to control for the demographic differences of the counties. The employment shares by sector for agriculture, mining, and manufacturing, unemployment rate, mean household income, and share of the population with a college degree are included to control economic differences across counties. Both pre-election levels and pre-trends for those variables are included in the models. I also include state level fixed effects $D_s$. Above base model is altered by including a an interaction term with a dummy for counties in states which ship soybeans predominantly via PNW posts as given below. I exclude the counties which are split between more than one congressional district. Further uncontested counties are controlled using dummy variables.

In order to test whether the soybeans tariff effect is heterogeneous, depending on the electoral competition in counties, I estimate the following flexible triple-interaction model following (Blanchard, Bown, and Chor, 2019).

$$\begin{aligned}
\Delta Outcome_c^{16,18} = \alpha &+ \sum_b^6 \beta_1^b \mathbf{1}(c \in B^b) \times TS_c^{US,China} + \sum_b^6 \beta_2^b \mathbf{1}(c \in B^b) \times MFPSubsidy_c \\
&+ \sum_b^6 \beta_3^b \mathbf{1}(c \in B^b) \times TS_c^{US,China} \times MFPSubsidy_c \\
&+ \sum_b^6 \beta_4^b \mathbf{1}(c \in B^b) \times \Delta RealWage + \gamma \mathbf{X}_c \\
&+ D_s + \epsilon_c
\end{aligned} \tag{3}$$

where $\mathbf{1}(c \in B_b)$ is an indicator of the competitiveness bin based on six county vote share ranges of Trump in 2016. Here b = 1,2,..., 6 are the set of counties where the 2016 Trump vote share was 0-30%, 30-40%, 40-50%, 50-60%, 60-70%, and 70-100%.

Following flexible triple interaction model is estimated to determine the heterogeneous effect

[10]In the first round of MFP, \$1.65 per soybeans bushel was disbursed.

of soybeans tariff based on the dependence of counties on PNW ports.

$$\begin{aligned}\Delta Outcome_c^{16,18} = \alpha &+ \sum_p^2 \beta_1^p \mathbf{1}(c \in PNW^p) \times TS_c^{US,China} + \sum_b^2 \beta_2^p \mathbf{1}(c \in PNW^p) \times MFPSubsidy_c \\ &+ \sum_b^2 \beta_3^p \mathbf{1}(c \in PNW^p) \times TS_c^{US,China} \times MFPSubsidy_c \\ &+ \sum_b^2 \beta_4^p \mathbf{1}(c \in PNW^p) \times \Delta RealWage + \gamma \mathbf{X}_c \\ &+ D_s + \epsilon_c \end{aligned} \tag{4}$$

where $\mathbf{1}(c \in PNW^p)$ is an indicator of the group, which belongs particular county . The groups are p=1,2 where 1 = PNW and 2 = non-PNW.

I weight regressions by population to avoid over-representation of the rural counties. I cluster the standard errors two-ways by state and by commuting zone (CZ) to allow correlated shocks with residuals.Though I have controlled for most of the possible determinants of voting behavior, there are threats to the causality in the study. Mainly, Fajgelbaum et al. (2020) and Fetzer and Schwarz (2019) show that 2018 tariff incidence highly correlates with Republicans' election performance in 2016. This correlation implies that 2018 tariffs cannot be taken as independent from future U.S. political considerations (Blanchard, Bown, and Chor, 2019).

# 4 Data

Data for election results are from Dave Leip's Atlas. Data for county level MFP crops subsidy per worker and U.S. tariff protection per worker are taken from data set which is made available to public by Blanchard, Bown, and Chor (2019). Soybeans sales and production data are taken from the query tool of National Agricultural Statistics of USDA USDA (2019b). Data for health insurance variables are taken from American Community Survey (ACS). Other demographic and economic variables are mostly from U.S. Census. Finally, the percentage of real wage changes variable is taken from model based estimates done by Fajgelbaum et al. (2020) which is made available with the paper.

# 5 Results and Discussion

The descriptive statistics of some selected variables are given in table 3. The average Republican vote share loss in 2018 compared to 2016 is 6.3%. County level per worker exposure to Chinese soybeans tariff is \$220 on average while per worker tariff protection is \$218 on average. MFP crop subsidy disbursement varies highly based on the structure of crops production of each county. Per worker MFP crop subsidy is \$399.

Table 3: Descriptive statistics of key variables

| Variable | Mean | Standard Deviation |
|---|---|---|
| Republican vote share (2016-2018)[1] | -0.063 | 0.125 |
| Republican vote share -2018 Congressional[1] | 0.629 | 0.191 |
| Republican vote share -2016 Congressional[1] | 0.690 | 0.221 |
| Republican vote share-2016 Presidential[1] | 0.667 | 0.161 |
| Soy tariff by China [2] | 0.220 | 0.600 |
| MFP crop subsidy [2] | 0.399 | 1.044 |
| U.S. tariff protection[2] | 0.218 | 0.370 |
| Real wage effect [3] | -1.030 | 0.539 |

[1] Not weighted by population.
[2] Values are given in $ 1000 per worker.
[3] Percentage change of real wage. This is a model based estimate by (Fajgelbaum et al., 2020).

Baseline estimates show that, soybeans tariff imposed by China has a significant negative association with the Republican vote share change between 2016 and 2018. The coefficient is largely stable in all the four columns in table 4. In column 2 I add health insurance variables as health insurance was an important issue in 2018 congressional election. In column 3 and column 4 U.S. tariff protection is replaced by the overall real wage effect of 2018 trade stemmed to input-output linkages. Another important finding in the baseline estimation is that MFP crop subsidy has a positive effect on the vote share change. However I do not find any significant effect of the interaction between soybeans tariff and MFP crop subsidy. It implies, there is no dampening effect of MFP on the negative effect of Chinese soybeans tariff on Republican vote share change between 2016 and 2018.

Table 4: Effect of Chinese Soybeans Tariff on Republican Vote Share Change 2016-2018

| VARIABLES | (1)<br>Model 1 | (2)<br>Model 2 | (3)<br>Model 3 | (4)<br>Model 4 |
|---|---|---|---|---|
| Soybeans Tariff | -0.021* | -0.021* | -0.022** | -0.022* |
| | (0.011) | (0.011) | (0.011) | (0.011) |
| Soybeans Tariff × MFP C. | -0.002 | -0.002 | -0.002 | -0.002 |
| | (0.002) | (0.002) | (0.001) | (0.002) |
| MFP C. | 0.021*** | 0.021*** | 0.021*** | 0.021*** |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| US Tariff Protection | -0.004 | -0.003 | | |
| | (0.005) | (0.005) | | |
| Insured population (Share) | | -0.063 | | -0.073 |
| | | (0.116) | | (0.117) |
| Δ Insured population (Share) | | 0.021 | | 0.028 |
| | | (0.086) | | (0.089) |
| Δ Real Wage | | | -0.004 | -0.004 |
| | | | (0.004) | (0.004) |
| | (0.237) | (0.232) | (0.233) | (0.229) |
| Observations | 2,633 | 2,633 | 2,580 | 2,580 |
| R-squared | 0.806 | 0.806 | 0.807 | 0.807 |
| State FEs | Y | Y | Y | Y |
| Weighted | Y | Y | Y | Y |
| Other Controls | Y | Y | Y | Y |

Standard errors are clustered by State and CZ
*** p<0.01, ** p<0.05, * p<0.1

The degree of the association between the soybeans tariff and Republican vote share change across competitive bins is vastly heterogeneous. An important outcome is that China's soybeans tariff has a disproportionately negative association with the Republican vote share change in the counties which belong to (0.4,0.5] competitive bin. The estimate t is larger than the comparable estimate in baseline model. The coefficient varies from -0.201 to -0.187 (Table 5). That estimate implies that for one standard deviation increase of Chinese soybeans tariff (0.600), is associated with $0.600 \times 0.201 \approx 12$ % vote share loss for Republicans in the (0.4,0.5] competitive bin. The last estimate is nearly twice the average vote share loss of the Republicans in 2018 compared to 2016 (Table 3). Statistically significant but small negative association exist between soybeans tariff and Republican vote share in (0.7,1] competitive bin. We can explain the larger negative association in (0.4,05] competitive bin by the hypothesis that voters in competitive counties are closer to be on an indifferent point between political parties . The electoral competition via trade policy disadvantaged the Republicans due to retaliation by China in the (0.4,05] because marginal negative effect of retaliatory tariff on Republican vote share among voters closer to be on an indifferent point is relatively higher. The voters in this bin might have preferred a party with less economically harmful trade policy over Republicans.

Table 5: Effect of Chinese Soybeans Tariff on Republican Vote Share Change 2016-2018 by competitive bins

| VARIABLES | (1) Model 1 | | (2) Model 2 | |
|---|---|---|---|---|
| Soy. Tariff $\times 1(\text{Pres.Vote} \in [0,0.3])$ | -0.369 | (0.421) | -0.759 | (0.702) |
| Soy. Tariff $\times 1(\text{Pres.Vote} \in (0.3,0.4])$ | 0.084 | (0.065) | 0.046 | (0.062) |
| Soy. Tariff $\times 1(\text{Pres.Vote} \in (0.4,0.5])$ | -0.201** | (0.099) | -0.187** | (0.089) |
| Soy. Tariff $\times 1(\text{Pres.Vote} \in (0.5,0.6])$ | 0.016 | (0.127) | -0.037 | (0.127) |
| Soy. Tariff $\times 1(\text{Pres.Vote} \in (0.6,0.7])$ | 0.032 | (0.019) | 0.032* | (0.018) |
| Soy. Tariff $\times 1(\text{Pres.Vote} \in (0.7,1])$ | -0.021** | (0.010) | -0.025** | (0.012) |
| MFP C. $\times 1(\text{Pres.Vote} \in [0,0.3])$ | 0.336*** | (0.096) | 0.135 | (0.088) |
| MFP C. $\times 1(\text{Pres.Vote} \in (0.3,0.4])$ | -0.010 | (0.050) | -0.010 | (0.039) |
| MFP C. $\times 1(\text{Pres.Vote} \in (0.4,0.5])$ | 0.028 | (0.089) | -0.035 | (0.109) |
| MFP C. $\times 1(\text{Pres.Vote} \in (0.5,0.6])$ | -0.009 | (0.098) | 0.059 | (0.099) |
| MFP C. $\times 1(\text{Pres.Vote} \in (0.6,0.7])$ | -0.022* | (0.012) | -0.022** | (0.010) |
| MFP C. $\times 1(\text{Pres.Vote} \in (0.7,1])$ | 0.024*** | (0.004) | 0.019*** | (0.005) |
| Soy. Tariff $\times$ MFP C. $\times 1(\text{Pres.Vote} \in [0,0.3])$ | 0.064 | (0.257) | 0.475 | (0.456) |
| Soy. Tariff $\times$ MFP C. $\times 1(\text{Pres.Vote} \in (0.3,0.4])$ | -0.036*** | (0.012) | -0.025* | (0.014) |
| Soy. Tariff $\times$ MFP C. $\times 1(\text{Pres.Vote} \in (0.4,0.5])$ | 0.038 | (0.042) | 0.061 | (0.048) |
| Soy. Tariff $\times$ MFP C. $\times 1(\text{Pres.Vote} \in (0.5,0.6])$ | -0.002 | (0.003) | -0.007* | (0.004) |
| Soy. Tariff $\times$ MFP C. $\times 1(\text{Pres.Vote} \in (0.6,0.7])$ | -0.000 | (0.003) | -0.000 | (0.003) |
| Soy. Tariff $\times$ MFP C. $\times 1(\text{Pres.Vote} \in (0.7,1])$ | -0.002 | (0.002) | -0.001 | (0.002) |
| $\Delta$ Real Wage $\times 1(\text{Pres.Vote} \in [0,0.3])$ | | | -0.056*** | (0.014) |
| $\Delta$ Real Wage $\times 1(\text{Pres.Vote} \in (0.3,0.4])$ | | | -0.030** | (0.011) |
| $\Delta$ Real Wage $\times 1(\text{Pres.Vote} \in (0.4,0.5])$ | | | -0.030* | (0.017) |
| $\Delta$ Real Wage $\times 1(\text{Pres.Vote} \in (0.5,0.6])$ | | | 0.007 | (0.011) |
| $\Delta$ Real Wage $\times 1(\text{Pres.Vote} \in (0.6,0.7])$ | | | 0.004 | (0.005) |
| $\Delta$ Real Wage $\times 1(\text{Pres.Vote} \in (0.7,1])$ | | | -0.001 | (0.005) |
| Observations | 2,633 | | 2,580 | |
| R-squared | 0.814 | | 0.815 | |
| State FEs | Y | | Y | |
| Weighted | Y | | Y | |
| Other Controls | Y | | Y | |

Standard errors are clustered by State and CZ
*** p<0.01, ** p<0.05, * p<0.1

Table 6 shows the heterogeneous association of soybeans tariff with Republican vote share change across counties that ship soybeans through PNW ports. As expected , the association between soybean tariff exposure and Republican vote share change in PNW counties, is negative and significant. The coefficient is stable across the models which accounts for tariff protection and overall wage effect of 2018 tariff war separately. One standard deviation of soybeans tariff (0.600) is associated with $0.600\times$ -0.022 = 1.3% Republican vote share loss.

Table 6: Differential Effect of Chinese Soybeans Tariff on Republican Vote Share Change 2016-2018 in Counties that ship through PNW

| VARIABLES | (1)<br>Model 1 | | (2)<br>Model 2 | |
|---|---|---|---|---|
| Soy. Tariff × PNW | -0.022** | (0.010) | -0.029*** | (0.008) |
| Soy. Tariff × non-PNW | 0.012 | (0.015) | 0.009 | (0.015) |
| MFP C. × PNW | 0.025*** | (0.004) | 0.025*** | (0.004) |
| MFP C. × non-PNW | 0.012 | (0.009) | 0.012 | (0.009) |
| Soy. Tariff × MFP C. × PNW | -0.002 | (0.001) | -0.001 | (0.001) |
| Soy. Tariff × MFP C. × non-PNW | -0.017** | (0.008) | -0.015** | (0.007) |
| US Tariff Protection × PNW | -0.009 | (0.009) | | |
| US Tariff Protection × non-PNW | -0.003 | (0.005) | | |
| Δ Real Wage × PNW | | | -0.013 | (0.013) |
| Δ Real Wage × non-PNW | | | -0.003 | (0.004) |
| Observations | 2,633 | | 2,580 | |
| R-squared | 0.807 | | 0.807 | |
| State FEs | Y | | Y | |
| Weighted | Y | | Y | |
| Other Controls | Y | | Y | |

Standard errors are clustered by State and CZ
*** p<0.01, ** p<0.05, * p<0.1

# 6 Conclusion

The 2018 Congressional election was held when U.S. and China involved in a trade war. While empirical studies showed that 2018 trade war was costly for both partners, I investigated the electoral effect of Chinese soybeans tariff on the Republicans and its heterogeneity across counties based on the degree of electoral competition and across U.S. regions. Using county level election data and soybeans tariff exposure variable I found significantly negative and spatially heterogeneous association between soybeans tariff and Republican vote share change between 2016 and 2018. Specially I found that tariff effect is more prominent in counties where Trump's vote share was between 40%-50% in 2016. It shows that it is effective if the voters who are closer to be on an indifference point between Republican party and Democratic party, are targeted in trade policy (retaliation in this case). Further, I found a significant and relatively large negative association between Chinese soybean tariff and Republican vote share change in counties which ship soybeans through PNW ports. I did not find a significant effect of MFP subsidies in mitigating the electoral harm done by soybeans tariff. This study implies that populist protectionist policies tend to backfire in an increasingly globalized world at least when the retaliating trade partner buys a significant amount of goods from the protectionist country.

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# Appendix A

Table A1: Soybeans Surplus Regions and their supply/export regions

| Region | States | Surplus market |
|---|---|---|
| Upper Mississippi | Illinois and Iowa | Barge to Gulf,rail to Southeast |
| OIMK | Ohio, Indiana, Michigan, Kentucky | Predominately supplies grain flows to the North Atlantic, Mid-Atlantic and Southeast transport regions, and sends surplus supplies down the Ohio and Mississippi River Systems to the Lower Mississippi region |
| Northern Plains | Minnesota, Montana, North Dakota, South Dakota and Wisconsin | Heavily dependent on rail transport, primarily accessing PNW ports |
| Central Plains | Colorado, Kansas, Nebraska and Wyoming | Ship to export markets through the PNW, Texas Gulf, Southwest feed markets |

Table A2: Percentage of Soybeans Moved to Export Positions in key soybeans producing states

| State | Export Position Barge [1] | Export position Rail[2] | | | |
|---|---|---|---|---|---|
| | Center Gulf | Center Gulf | PNW | Texas Gulf | Atlantic |
| Arkansas | 98 | 60 | 0 | 0 | 0 |
| Illinois | 93 | 53 | 14 | 4 | 20 |
| Indiana | 93 | 36 | 5 | 0 | 0 |
| Iowa | 91 | 10 | 80 | 2 | 20 |
| Kansas | | 29 | 0 | 51 | 0 |
| Kentucky | 93 | 60 | 0 | 0 | 0 |
| Michigan | | 88 | 0 | 0 | 0 |
| Mississippi | 97 | 60 | 0 | 0 | 0 |
| Minnesota | 91 | 2 | 91 | 0 | 0 |
| Nebraska | | 11 | 81 | 4 | 0 |
| North Dakota | | 2 | 92 | 0 | 0 |
| Ohio | 94 | 48 | 0 | 0 | 48 |
| South Dakota | | 5 | 90 | 0 | 0 |
| Wisconsin | 96 | 4 | 76 | 0 | 0 |

[1] (100-Export Position Barge) is soybeans percentage transported on barges domestically
[2] (100-Export Position Rail) is soybeans percentage transported on train domestically

States in Northern and Central Plains regions of U. S.

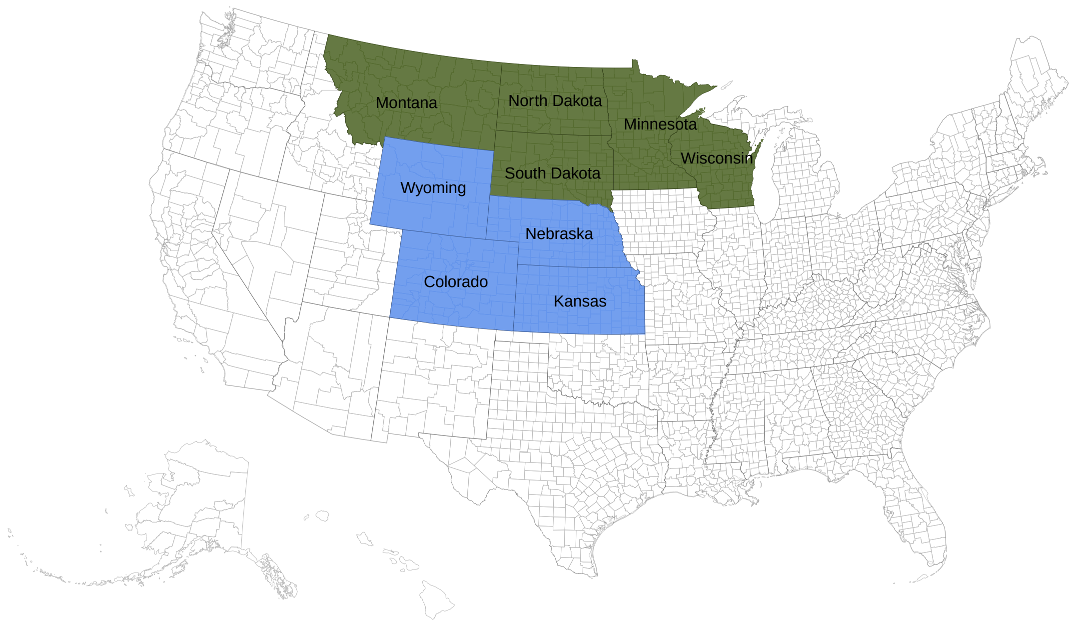


Figure A1: States in the Northern and Central Plains