ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Master Thesis International Economics

Title thesis: *The impact of Trump's Trade War on the 2020 United States presidential election through import production, retaliation, and input costs channel*

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Abstract

In the 2020 presidential election, Donald Trump's overall number of votes has increased in every state. His presidency has been associated with an unprecedented increase in trade barriers for the 21st century. In this paper, I try to answer the question of the impact of Donald Trump’s Trade War between 2018-2019 on the 2020 United States presidential election through the channels of import production, retaliation, and intermediate input costs. To examine it, I employ data on tariffs and election results from David Leip’s Election Atlas and Flaaen and Pierce (2019). Using the fixed effects regression model, I find significant results for import protection and retaliation channel. I conclude that tariffs had varied, albeit negligible effects on the 2020 election outcome.

1. Introduction

In the 2020 presidential election in the United States of America, Republican party candidate Donald Trump has received almost 75 million votes, increasing his total vote in every state (Byler, 2021). Trump's presidential term between 2017 to 2021 has been characterized by trade protectionism with the most recognizable examples of new tariffs on steel, aluminum, and a broad range of Chinese products. One of the prime justifications of this trade policy was to protect domestic manufacturing jobs from Chinese competition. During the 1st presidential debate in 2020, Donald Trump has claimed that he brought back 700,000 manufacturing jobs (CNBC, 2020). If his policy was indeed successful, the increase in tariffs could have resulted in more support for Trump's candidacy from the workers and manufacturers, who benefitted from increased import protection and can at least partially explain the increase in the total amount of votes cast for him. On the other hand, this approach triggered negative consequences for the American economy - retaliation from its most important trading partners such as Canada, Mexico, China, the EU. Furthermore, additional trade barriers made intermediate inputs more expensive, which potentially disadvantaged manufactures' competitiveness abroad and domestically. Clearly, these introduced protectionist measures have a broad range of economic implications. However, without empirical analysis, it can be quite complicated to precisely state which one of the described effects dominated over the others and how it has transformed into the political preferences of individuals. Therefore, in my paper, I examine the consequences of the US trade policy with the question of the impact of Donald Trump's Trade War between 2018-2019 on the 2020 United States presidential election through the channels of import production, retaliation, and intermediate input costs. This specific period is investigated because starting 2018 President Trump considerably raised tariffs against the largest trading partners of the United States. In September 2018, these duties already accounted for over 12% of US imports (Bown, 2019).

Many studies already exist, which examine the influence of tariffs on US domestic politics (Autor, Dorn, & Hanson, 2013; Che, Lu, Pierce, Schott, & Tao, 2016). However, my work will be employing the new 2020 election dataset, providing the most recent insights, and concentrating on the presidential elections rather than congressional outcomes (e.g., Blanchard, Bown, & Chor, 2019). Opposed to Choi and Lim (2021), who already employ the 2020 dataset, this analysis will extend beyond the agricultural sector and Chinese retaliation by considering data on the manufacturing sector and retaliation from other countries, e.g., Canada, Mexico, European Union. As in Lake and Nie (2021), I will control for the impact of the Covid-19 pandemic, but I will expand beyond the generalized impact of all tariffs. I attempt to account for the effect of the tariffs on the manufacturing sector between years 2018 to 2019 through three distinctive ways, which are import production, retaliation, and intermediate input costs. Flaaen & Pierce (2019) have already distinguished the impact of 2018-2019 tariffs through these channels on manufacturing employment, industrial output, and producer prices. Nonetheless, the scholars focused solely on economic outcomes, and I intend to analyze their political effects.

With this research, policymakers will be able to better identify and predict social and political consequences of their trade policies that extend beyond purely economic effects, if we are to assume that citizens reveal their preferences with their voting choices. Observations from manufacturing industries are particularly relevant because this sector has a major impact on the American economy being the 5th largest US employer (U.S. Census Bureau, 2020).

In the empirical part, I employ a fixed regression strategy, which exploits the cross-county variation in industries' employment. The dependent variable is the presidential vote share difference between 2020 and 2016 for the Republican party, whereas the independent variable is the county's weighted estimate of import protection, retaliation, and input costs. I proceed to confirm the plausibility of my results with three additional regressions. The first one focuses on the 2020 Senate vote results and the second one considers the presidential vote share difference between 2016 and 2012. Third regression analysis is performed using a sample without outliers. I conclude that import protection and retaliation channel had a statistically significant, but small impact on the Republican vote share, which is negative and positive in that order. The main implication of my study is that the relationship between economic gains and losses from trade policies and support for politicians is very convoluted. However, in that context, my research managed to confirm past studies, which show that trade policies have an impact on domestic politics in the United States.

I begin this paper with a literature review, where I present and discuss the most prominent findings on the economic and political effects of US tariffs. Then, I describe the data employed in my study that concerns the 2020 US election results and disentangled effects of tariffs. I proceed with the methodology section, where I explain and justify the choice of the empirical strategy applied, that is a regression estimate with fixed effects. I further perform additional robustness checks, discuss the results, and conclude with the summary of my research, its limitations and recommendation for further analysis.

2. Literature review

2.1 Economic consequences of tariffs

There exists extensive literature discussing the economic consequences of Donald Trump's tariffs in the USA. In theory, a large country may increase its welfare with the introduction of a tariff because of an increase in producer surplus, which should inflict declining world prices and lead to the increase in output and employment, and greater government revenue. However, recent empirical research mainly emphasizes the negative economic effects of these trade barriers.

Handley, Kamal and Monarch (2020) utilize firm-level microdata and provide empirical evidence that the 2018-2019 tariffs significantly lowered the United States export growth. According to the authors, this result stems from the role of global supply chains and input intermediate goods, which represent almost 57% of the total value of goods affected by tariffs and retaliation. Flaaen and Pierce (2019) claim that the 2018 tariffs are linked to a decrease in manufacturing jobs and an increase in producer prices. Therefore, the tariff incidence has almost completely fallen on importers and consumers due to price increases of intermediate, and thus final goods (Amiti, Redding, & Weinstein, 2019; Amiti, Redding, & Weinstein, 2020).

Similarly, Cavallo, Neiman, Gopinath, and Tang (2019) analyzed import tariffs on Chinese products and found evidence that American producers experienced the greatest adverse effects. In contrast to previous studies, there is no clear indication that the retail price for consumers has increased as a short run response. It can be explained by willingly reduced profit margins by US retailers, which would again imply larger losses on the producers' side. In this case, factory and plant workers are also going to be adversely impacted by the increase in tariffs. Fajgelbaum, Goldberg, Kennedy and Khandelwal (2020) quantify the aggregate real net income loss due to tariffs to $7.2 billion, equal to 0.04% of GDP. All the articles confirm the importance of the intermediate input channel. Therefore, it is expected that rising input costs would decrease the share of votes cast for the incumbent president of the United States.

Regarding the benefits of imposed trade barriers, Flaaen, Hortacsu, and Tintelnot (2019) claim that the safeguard measure on imports of washing machines indeed had a positive influence on domestic production and employment in the USA because of the relocation of multinationals. This implies that the increased import protection should have led to the increase in the support of Donald Trump. Nonetheless, the overall net effect for the American economy remains negative due to higher consumer prices, but only when considering both washing machines with their complementary products. Waugh (2019) reached the opposite conclusion, which indicates that the US-Chinese trade war led to the loss in tradeable and retail employment after a fall in consumption. In his paper, he referred to changes in the US and Chinese trade policy between 2017 and 2018 and utilized auto sales data. Hence, the share of votes in favor of the president in counties with a sizeable industry base affected by retaliation is predicted to be lower. Since both articles describe the employment effects of trade but for specific products, their findings cannot be extrapolated to the whole manufacturing sector, which is what I strive to achieve with my analysis.

2.2 Political implications of trade and tariffs

Previous studies confirm that the economic gains and losses from trade policies directly influence election outcomes. According to the Heckscher-Ohlin model, trade can lead to a redistribution of income between different factors of production, thus create tensions within society and exacerbate polarization. Jensen, Quinn and Weymouth (2017) prove that counties with high levels of high-skilled employment are more likely to vote for the incumbent president in comparison to counties with low-skilled labour. Autor, Dorn, Hanson, and Majlesi (2020) consider congressional election results in the USA between 2002 to 2010, therefore immediately after China’s accession to World Trade Organization, and presidential elections result in 2000, 2008 and 2016. Their empirical research shows that more trade exposed districts elected more extreme Republic and Democratic candidates. Related research by Che, Lu, Pierce, Schott, and Tao (2016) extends the studied period of congressional votes from 1992 to 2010 and concludes that in counties more exposed to increased Chinese competition Democratic party candidates received a larger share of votes and were more likely to be elected for the U.S. House of Representatives. It is critical to note that at that time Democrats were more prone to support trade barriers and trade adjustment programs relative to the Republican party, which has been revised by the 2016 elections. Again, this evidence shows that more import protection ought to be reflected in a stronger approval of the president, who introduced more protectionist measures.

In the 2018 congressional elections, Republicans incurred electoral losses in counties most affected by foreign retaliation, especially on agricultural products (Blanchard et al., 2019). Chyzh and Urbatsch (2019) find the same evidence when utilizing data on soybeans production. Tariff protection and agricultural subsidies did not manage to offset the negative effect of retaliation. On the contrary, Choi & Lim (2021) argue that agricultural subsidies outweighed Chinese retaliatory tariffs and allowed Republican party to increase its vote share in the 2020 presidential election. Regarding the 2018-2019 tariffs' distributional effects, Fajgelbaum, Goldberg, Kennedy and Khandelwal (2020) concluded that import tariffs were imposed in favor of electorally competitive counties, whereas foreign retaliation targeted Republican counties. Evidence from Fetzer and Schwarz (2021) confirms that retaliatory measures were in introduced in way that would maximally hurt President Trump's voting base. According to these articles, retaliation should eventually lower Trump's election outcome in the most adversely affected counties.

3. Data

3.1 Data on election results

To investigate the effect of manufacturing tariffs on US election outcomes, I will utilize data on election results sourced from Dave Leip's Atlas of US Presidential Elections. It is an online database, which contains detailed information on the share of popular votes, electoral votes, and voter turnout for US presidential elections from 1789 till 2020 and US senate and gubernatorial elections since 1990 for Democratic, Republican, and third-party candidates. It includes results on a county level for all states excluding Alaska, which uses boroughs as its administrative units. In my analysis, I employ data covering the share of votes cast for Republic party candidates in presidential elections in 2012, 2016 and 2020. These years correspond with the timeline of President Trump's trade war. Specifically, I calculate the change in the share of votes cast for the Republican candidate as the difference between the years 2020 and 2016 and then from 2016 to 2012. For my robustness checks, I extract additional data on the share of votes cast for the Republic party candidate in the presidential election in 2008, and in the senate elections in 2016, 2018 and 2020. This data is available for most of the states but not for all of them since the whole senate is never elected at the same time.

3.2 Data on the impact of tariffs

To account for the impact of tariffs for different industries, I employ estimates on industry-level measures of exposure to import protection, retaliation, and rise in intermediate input costs. This data is entirely sourced from Flaaen and Pierce (2019). It is the most recent and comprehensive paper which quantifies the effect of the 2018-2019 US tariffs on the manufacturing sector through these three channels. Authors consider tariffs from the year 2018 to 2019, which is when the trade war mostly escalated. Already in 2019, the United States ended aluminum and steel tariffs for Canada and Mexico, whereas in 2020, the US signed a phase one deal with China (Bown & Kolb, 2021). These protectionist measures cover machines and solar panels/modules (Section 201), steel and aluminum (Section 232), tariffs on U.S. imports from China (Section 301) and numerous retaliatory measures. Throughout the analysis, authors refer to four-digit NAICS industry codes and I follow this standard for other variables in my paper, such as labor shares and control variables. Flaaen and Pierce (2019) estimate industry-level measures of trade policy impact for the cumulative set of tariffs for the import share of domestic absorption, export share of output, and share of costs. I elaborate more on each type of measure in the following section.

New protectionist measures can restrain foreign competition, thus positively affect domestic economic activity. Import share of domestic absorption measures the extent of import protection for a given industry by relating the scale of cumulative product-country pairs' imports affected by new tariffs to the level of domestic absorption. If US trading partners decide to impose retaliatory tariffs, then American competition will decrease abroad. The export share of output indicates the share of the industry's output that has been impacted by this type of countermeasure, interpreted as the industry's exposure to foreign retaliation. Finally, the last channel is the industry's share of intermediate input costs subject to new tariffs, otherwise interpreted as rising input costs. They occur when tariffs are levied on commodities, which constitute a significant share in the production mix of final goods, leading to higher production costs for American manufacturers. I restrict my analysis to the values of the top ten industries affected through each channel. This is necessary because not all the estimates have been published by the authors. Then, I assume that the tariff values for other industries are equal to 0.

Following previous literature (e.g., Blanchard et al., 2019; Choi, & Lim, 2021), I construct variable $Import\ Protection_c$. It represents aggregated import protection value across industries i in county c. To account for the importance of industry i in county c and to avoid over-representation of rural voters, the value of import protection in industry i is weighted with the amount of county's labor employed in that industry divided by the total county's employment, $\frac{L_{c,i}}{L_c}$. Then, it yields:

$$Import\ Protection_c = \sum_i \frac{L_{c,i}}{L_c} Import\ Protection_i$$

$Foreign\ Retaliation\ _c$ variable identifies aggregated exposure to foreign retaliation across industries i in county c. Correspondingly, the value of a foreign retaliation in industry i is weighted with the amount of county's labor employed in that industry divided by the total county's employment, $\frac{L_{c,i}}{L_c}$. This transformation results in:

$$Foreign\ Retaliation_c = \sum_i \frac{L_{c,i}}{L_c} Foreign\ Retaliation_i$$

The third variable $Rising\ Input\ Costs_c$ indicates aggregated rising intermediate input costs due to an increase in tariff across industries i in county c. As above, the value of rising input costs in industry i is weighted with the amount of county's labor employed in that industry divided by the total county's employment, $\frac{L_{c,i}}{L_c}$., leading to:

$$Rising\ Input\ Costs_c = \sum_i \frac{L_{c,i}}{L_c} Rising\ Input\ Costs_i$$

All employment values are assigned according to the NAICS industry codes and are obtained from the 2016 US County Business Patterns dataset, which collected the employment data during the week of March 12, 2016. US County Business Patterns is an annually updated database, which also contains data on numerous other economic indicators (first quarter payroll, annual payroll, number of establishments) by industry at the national, state and county levels. The year 2016 is chosen as the pre-sample year such that employment values are exogenous to tariff variables. In some circumstances, only a range of employees was specified and not a concrete number. Then, to get a rough estimate of employment, I took the average of the minimum and maximum values.

3.3 Additional data

I control for the pre-election demographic levels for the year 2016, and their pre-trends between 2016 and 2013. These are county's population shares by age groups, gender, and race. Other socioeconomic measures include the share of the population with a bachelor's degree or higher, unemployment rate and (log) mean household income. Throughout the analysis, I consider their average pre-election levels from the years 2015-2019, and their pre-trends between 2015-2019 and 2010-2014, following the strategy of Blanchard et al. (2019). To minimize the threat of potential noise in yearly reporting, the variables comprise 5-year average estimates. All controls originate from the United States Census Bureau's American Community Survey, which contains detailed population and housing information about US citizens. Data on Covid-19 county-level number of cases per 10,000 inhabitants marks the incidence as of November 2, 2020, the day before the elections were held. It is provided by the USAFacts initiative, which collects Government data from over 70 sources on the American population and US governments' finances. All control variables are summarized in Table 2.

3.4 Descriptive statistics

Summary statistics for the three channels of tariffs' impact and voting variables are contained in Table 1. My main sample consists of 3,112 counties. The variable for Republican candidate US Senate vote share is an exception with only 1,249 counties because of inconsistencies in the time of election held. On average, the county's aggregated weighted import protection equals 0.17%. However, there exists a large discrepancy between counties with the highest value of 14.43% and the lowest of 0. Similar means are obtained for weighted foreign retaliation and weighted rising input costs, equal to 0.04% and 0.06% respectively. The difference between the minimum and maximum estimates for these two variables are slightly lower in comparison to import protection, with the highest values 3.26% and 8%. The mean difference between the Republican candidate vote share across years remains rather stable and oscillates around 2% to 3.5%. The data depicts considerable variation across counties between 2016 and 2020, with the largest and lowest vote share changes of around 50% and -50%. Therefore, in certain counties, around half of the population decided to shift their votes to other candidates. Regarding Table 2, the average county's population in 2016 was predominantly white, with the largest share of voters between the ages of 55 to 64 and 65 and over. According to the 5-year estimate, 22% of the population had a higher education on average.

Table 1. Descriptive statistics for tariffs variables and voting variables

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Import Protection	3,112	0.0017	0.0062	0	0.1443
Foreign Retaliation	3,112	0.0004	0.0013	0	0.0326
Rising Input Costs	3,112	0.0006	0.0021	0	0.08
Republican Presidential Vote Share (2016)	3,112	0.6311	0.1570	0.0409	0.9458
Republican Presidential Vote Share (2012)	3,112	0.5966	0.1479	0.0600	0.9586
∆ Republican Presidential Vote Share (2020 minus 2016)	3,112	0.0184	0.0355	-0.5019	0.5347
∆ Republican Presidential Vote Share (2016 minus 2012)	3,112	0.0345	0.0584	-0.5520	0.6695
∆ Republican Presidential Vote Share (2012 minus 2008)	3,112	0.0286	0.0309	-0.1030	0.2090
∆ Republican Senate Vote Share (2020 minus 2016)	1,249	0.0014	0.0662	-0.1725	0.3316

Table 2. Descriptive statistics for demographic and socioeconomic control variables

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Covid Incidence	3,112	290.0588	177.7168	0	1795.1470
Population share, Age 25-34 (2016)	3,112	0.1163	0.0224	0	0.268
Population share, Age 35-44 (2016)	3,112	0.1166	0.0158	0.033	0.208
Population share, Age 45-54 (2016)	3,112	0.1354	0.0150	0.026	0.248
Population share, Age 55-64 (2016)	3,112	0.1396	0.0225	0.032	0.448
Population share, Age 65 and over (2016)	3,112	0.1763	0.0446	0.039	0.531
Population share, Female (2016)	3,112	0.4998	0.0233	0.215	0.585
Population share, Black (2016)	3,112	0.0909	0.1456	0	0.862
Population share, White non-Hispanic (2016)	3,112	0.8370	0.1635	0.046	1
Population share, Hispanic (2016)	3,112	0.0899	0.1365	0	0.99
Unemployment rate (2015-2019 avg.)	3,112	0.0296	0.0130	0	0.1560
Log mean household income (2015-2019 avg.)	3,112	4.8340	0.0972	4.5541	5.2583
Share with some college (2015-2019 avg.)	3,112	0.2196	0.0958	0	0.7760
∆ Population share, Age 25-34 (2016 minus 2013)	3,112	0.0011	0.0104	-0.264	0.074
∆ Population share, Age 35-44 (2016 minus 2013)	3,112	-0.0037	0.0082	-0.063	0.074
∆ Population share, Age 45-54 (2016 minus 2013)	3,112	-0.0100	0.0096	-0.135	0.053
∆ Population share, Age 55-64 (2016 minus 2013)	3,112	0.0050	0.0086	-0.062	0.195

Δ Population share, Age 65 and over (2016 minus 2013)	3,112	0.0122	0.0113	-0.079	0.204
Δ Population share, Female (2016 minus 2013)	3,112	-0.0004	0.0092	-0.109	0.129
Δ Population share, Black (2016 minus 2013)	3,112	0.0005	0.0091	-0.19	0.126
Δ Population share, White non-Hispanic (2016 minus 2013)	3,112	-0.0042	0.0340	-0.788	0.944
Δ Population share, Hispanic (2016 minus 2013)	3,112	0.0046	0.0105	-0.187	0.116
Δ Log mean household income (2015-2019 minus 2010-2014)	3,112	0.0636	0.0347	-0.1844	0.3078
Δ Unemployment rate (2015-2019 minus 2010-2014)	3,112	-0.0560	0.0315	-0.2570	0.0430
Δ Share with some college (2015-2019 minus 2010-2014)	3,112	0.0194	0.1276	-0.5950	0.5690

4. Methodology

Using previously introduced variables $Import\ Protection_c$, $Foreign\ Retaliation_c$, and $Rising\ Input\ Costs_c$, I construct the main empirical fixed-effects model, which exploits the within-state, cross-county variation to estimate the effect of the 2018-2019 tariffs through these channels on the 2020 election results. Thus, the baseline specification is:

$$\Delta VoteR_c^{2020-2016} = \beta_1 Import\ Protection_c + \beta_2 Foreign\ Retaliation_c + \beta_3 Rising\ Input\ Costs_c + \delta CovidIncidence_c + \eta \Delta VoteR_c^{2016-2012} + \gamma VoteR_c^{2016} + \iota X_c + \varphi_s + \varepsilon_c,$$

where $\Delta VoteR_c^{2020-2016}$ is a continuous dependent variable ranging from 0 to 1, which shows a change in the county's Republican vote share between the 2020 and 2016 presidential elections. $Import\ Protection_c$, $Foreign\ Retaliation_c$, and $Rising\ Input\ Costs_c$ represent main independent continuous variables. The higher these values, the more import protection benefits, foreign retaliation burden, and input costs for industries located in a county c.

$CovidIncidence_c$ represents a continuous variable for COVID-19 cases per 10,000 inhabitants in each county. According to Fajgelbaum et al. (2019), the geographic incidence of tariffs is correlated with Republican party election performance. Furthermore, Baccini, Brodeur, and Weymouth (2020) suggest that in counties with a larger share of Republican voters, people are less likely to practice social distancing. Therefore, the pandemic variable is added to the model to control for any potential bias. $\Delta VoteR_c^{2016-2012}$ accounts for pre-existing trend as a change in the Republican vote share between the 2016 and 2012 presidential elections. $VoteR_c^{2016}$ refers to the Republican vote share in the 2016 Presidential election and is implemented in the model to control for the past voting behavior. X_c represents a set of pre-election control variables and trends, which allow to avoid the bias of an estimate, consisting of population shares by education, age, gender, race, (log) mean household income and the unemployment rate. My choice of the demographic and socioeconomic control variables follows the selection from Blanchard et al. (2019), which is based on a substantial amount of literature describing the determinants of electoral outcomes during the previous elections (Theiss-Morse, Wagner, Flanigan, & Zingale, 2018; Kondik, 2019; Shafer, & Wagner, 2018). In my analysis, I must assume that there are no other factors explaining the US voting patterns. φ_s is a state fixed effect, which accounts for different voting patterns between states. Variable ε_c depicts the error term.

In the model, I cluster standard errors by state to account for geographically correlated shocks. My sample includes all states and counties, except for Alaska and Kalawao county. Kalawao, the smallest county by population size and area, is excluded due to the scarcity of data. Whereas Alaska's administrative units do not match these from other states. Regarding the empirical assumptions, I must assume that there are no important characteristics of counties, which I do not account for with my set of controls variables, which could be correlated with the tariffs' impact variables and voting shares. This condition is not verifiable, nonetheless controlling for a variety of pre-election specifications and trends should greatly eliminate this threat. Additionally, the strategy requires that there is no reverse causality so that voting results do not influence county-level values of tariffs' import protection, retaliation, and input costs in any way. Considering that the 2020 presidential elections were held more than two years after the announcement of the first protectionist policy, this should not be a concern.

In addition, I graphically display the relationships between a change in the county's Republican vote share between the 2020 and 2016 presidential elections (y-axis) and import protection, foreign retaliation, or rising input costs (x-axis) using scatterplots.

5. Results

5.1 Main results

Previous studies described in the literature review section postulate three important propositions. Firstly, that more import protection should boost the outcome for a president that implemented these measures. Secondly, the support for the incumbent president will decrease in counties most adversely affected by foreign retaliation. Similarly, rising input costs will decrease the share of votes cast for that candidate. In the following paragraphs, I will analyze the empirical evidence for those statements utilizing the cross-county fixed effects regression model.

Main regression results are contained in Table 3. Column 1 presents estimates with full specification, Column 2 is without controls.

Table 3. Regression results for the relationship between the difference in the 2020-2016 Republican presidential vote share and the values of import protection, foreign retaliation, and rising input costs, with and without control variables

VARIABLES	(1) Δ Republican Presidential Vote Share (2020 minus 2016)	(2) Δ Republican Presidential Vote Share (2020 minus 2016)
Import Protection	-0.105**	-0.0762
	(0.0498)	(0.0749)
Foreign Retaliation	0.809*	0.758
	(0.444)	(0.492)
Rising Input Costs	-0.193	0.0156
	(0.167)	(0.225)
Republican Presidential Vote Share (2016)	-0.115***	-0.00359
	(0.0357)	(0.0209)
Δ Republican Presidential Vote Share (2016 minus 2012)	-0.103	0.0392
	(0.0916)	(0.0887)
Covid Incidence	1.06e-05	
	(6.44e-06)	
Population share, Age 25-34 (2016)	-0.244***	
	(0.0773)	
Population share, Age 35-44 (2016)	-0.0983	
	(0.0818)	
Population share, Age 45-54 (2016)	-0.268***	
	(0.0927)	
Population share, Age 55-64 (2016)	-0.157*	
	(0.0787)	
Population share, Age 65 and over (2016)	0.00487	
	(0.0414)	
Population share, Black (2016)	-0.0225	
	(0.0184)	
Population share, Female (2016)	-0.137***	
	(0.0385)	

Population share, Hispanic (2016)	0.0179	
	(0.0232)	
Population share, White non-Hispanic (2016)	0.0733***	
	(0.0270)	
Unemployment rate (2015-2019 avg.)	-0.245***	
	(0.0664)	
Log mean household income (2015-2019 avg.)	0.00306	
	(0.0187)	
Share with some college (2015-2019 avg.)	-0.247***	
	(0.0608)	
Δ Population share, Age 25-34 (2016 minus 2013)	0.136**	
	(0.0613)	
Δ Population share, Age 35-44 (2016 minus 2013)	0.319***	
	(0.115)	
Δ Population share, Age 45-54 (2016 minus 2013)	0.204**	
	(0.101)	
Δ Population share, Age 55-64 (2016 minus 2013)	0.0509	
	(0.118)	
Δ Population share, Age 65 and over (2016 minus 2013)	-0.0240	
	(0.0772)	
Δ Population share, Black (2016 minus 2013)	-0.163***	
	(0.0578)	
Δ Population share, Female (2016 minus 2013)	-0.00716	
	(0.0662)	
Δ Population share, Hispanic (2016 minus 2013)	-0.156*	
	(0.0792)	
Δ Population share, White non-Hispanic (2016 minus 2013)	-0.0152	
	(0.0721)	
Δ Share with some college (2015-2019 minus 2010-2014)	0.0141***	
	(0.00509)	
Δ Log mean household income (2015-2019 minus 2010-2014)	0.0263	
	(0.0186)	
Δ Unemployment rate (2015-2019 minus 2010-2014)	0.0762***	
	(0.0284)	
Constant	0.248***	0.0191
	(0.0876)	(0.0121)
State FEs	Y	Y
Observations	3,112	3,112
R-squared	0.338	0.006

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The negative coefficient for import protection variable suggests that in counties where industries gained from trade restriction, the support for the Republican president has decreased. Precisely, a one standard deviation increase in import protection leads to $0.105 \times 0.0062 \approx 0.07$ percentage points less in the Republican vote share on average. Its relative magnitude with regards to the mean of vote share change is 3.5% ($0.000651/0.0184 \approx 3.5\%$). Therefore, the effect is rather negligible. This estimate is statistically significant at the 5% level ($p<0.05$).

Higher exposure to foreign retaliation for county's industries implies a rise in the support for the Republican candidate. On average, a one standard deviation greater expansion in industries' exposure to foreign retaliation is followed by a growth in the vote share equal to $0.809 \times 0.0013 \approx 0.1$ percentage points. The relative magnitude of this effect is equal to 5.7%

(0.0010517/0.0184 ≈ 5.7%). Thus, it is greater than that of import protection, but still not substantial. The relationship is statistically significant at the 10% level ($p<0.1$).

Lastly, the negative coefficient implies that counties with industries more affected by the rising intermediate input prices are less likely to support the Republican presidential candidate, all else equal. A one standard deviation increase in the input costs leads to an average decline in the vote share of $0.193 \times 0.0021 \approx 0.04$ percentage points. The magnitude of the effect estimate against the mean vote share is 2.2% (0.0004053/0.0184 ≈ 2.2%). It is smaller than the magnitude of import protection and foreign retaliation, and again not considerable. Furthermore, the estimate is not statistically significant and economically meaningful.

The cumulative effect of one standard deviation changes for all the channels is close to 0 percentage points. Similarly, the aggregated effect of one standard deviation changes for all the channels with statistically significant estimates is almost 0, with 0.03 percentage points.

The restricted model without any controls propounds different estimates and direction of the relationship for the variable of rising input costs (Table 3, Column 2). Moreover, all coefficients are not statistically significant. Thus, the set of proposed controls should be preserved in the baseline regression specification. Otherwise, the coefficients differ greatly and are likely biased due to many omitted variables.

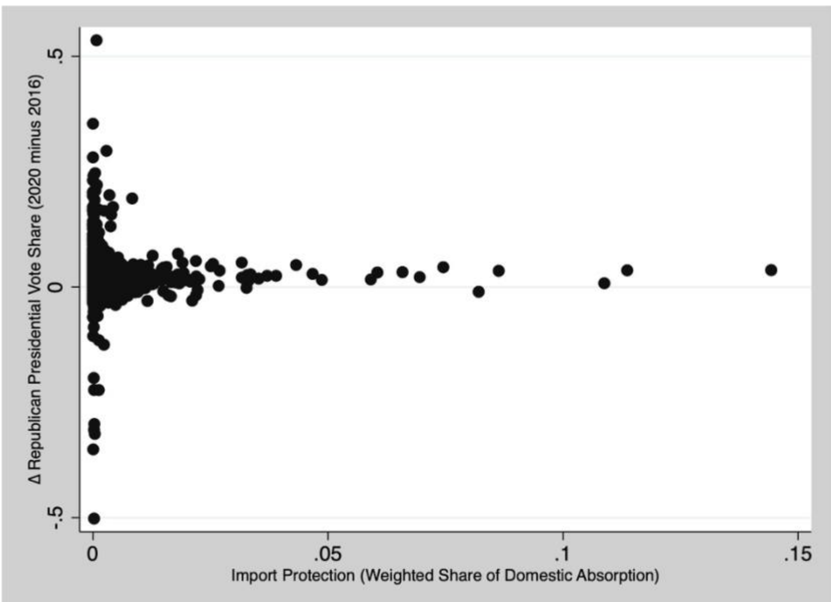

Figure 1. Scatterplot for the relationship between the difference in the 2020-2016 Republican presidential vote share and the values of import protection

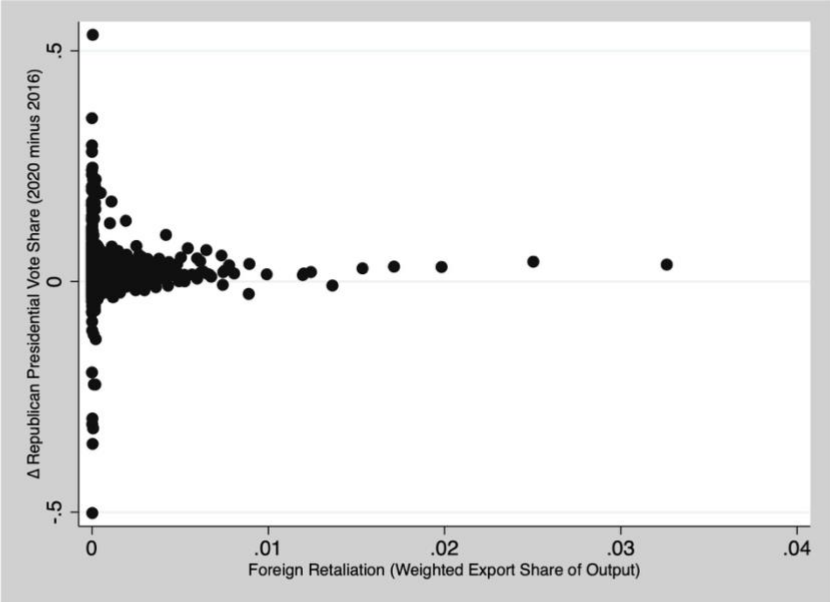

Figure 2. Scatterplot for the relationship between the difference in the 2020-2016 Republican presidential vote share and the values of foreign retaliation

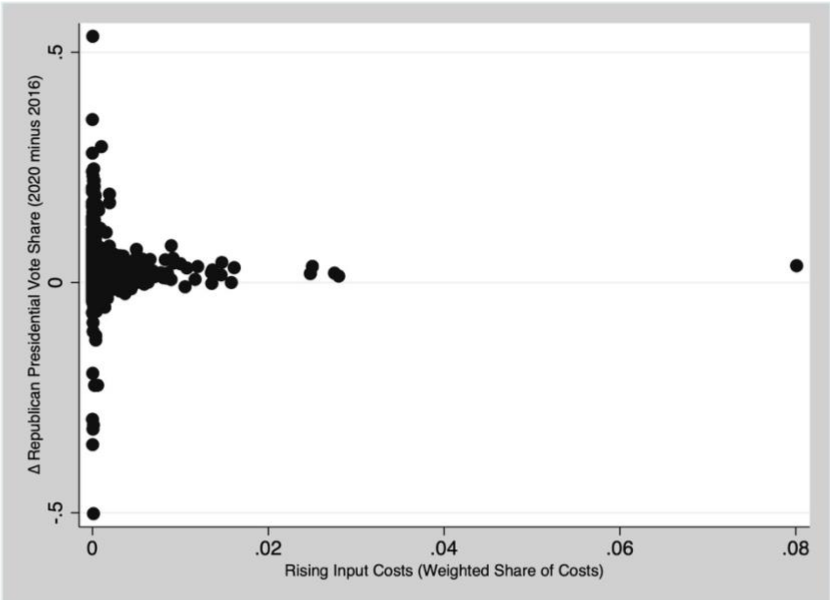

Figure 3. Scatterplot for the relationship between the difference in the 2020-2016 Republican presidential vote share and the values of rising input costs

Figures 1-3 depict scatterplots for the relationship between the difference in the 2020-2016 Republican presidential vote share and values of import protection, foreign retaliation, or rising input costs. No clear and strong relationships between variables emerge when looking at all three graphs. This conclusion is in line with the regression results, which demonstrate weak association for either import protection or foreign retaliation and vote share changes, and no statistically significant results between rising input costs and the rise in popularity of

Republican candidate. Furthermore, there are many observations clustered around the value of 0 for all three channels. It may partially explain why it is not possible to prove any strong relationship between variables, as the cumulative impact of tariffs is generally low with the chosen measures.

5.2 Robustness checks

To verify my results, I conduct three additional checks with adjusted regression models and samples. Firstly, I estimate the effect of increased county's import protection, foreign retaliation, and input costs on the difference in the vote share of the Republican candidate in the presidential elections between 2016 and 2012 instead of 2020 and 2016. Accordingly, I adjust the voting variables Republican presidential vote share to the year 2012 and Δ Republican Presidential Vote Share to 2008-2012. The rest of the variables remains the same as in the original description. All the variables of interest attempt to measure the effect of tariffs introduced between 2018-2019, so after the 2016 elections. Hence, the regression results should not indicate any type of connection between the three channels and election outcomes between 2016 and 2012. Table 4 shows the estimates for the modified model and indeed no statistically significant relationship is identified. Furthermore, the estimates of independent variables changed their direction in comparison to the main coefficients, from positive to negative for retaliation, and from negative to positive for input costs.

Table 4. Regression results for the relationship between the difference in the 2016-2012 Republican Presidential vote share and the values of import protection, foreign retaliation, and rising input costs with control variables

VARIABLES	(1) Δ Republican Presidential Vote Share (2016 minus 2012)
Import Protection	-0.0341
	(0.0978)
Foreign Retaliation	-0.430
	(0.613)
Rising Input Costs	0.343
	(0.332)
Republican Presidential Vote Share (2012)	-0.170***
	(0.0237)
Δ Republican Presidential Vote Share (2012 minus 2008)	-0.103
	(0.127)
Covid Incidence	2.60e-05**
	(1.12e-05)
Population share, Age 25-34 (2016)	0.0580
	(0.115)
Population share, Age 35-44 (2016)	0.244**
	(0.0943)
Population share, Age 45-54 (2016)	0.528*

	(0.280)
Population share, Age 55-64 (2016)	-0.174
	(0.120)
Population share, Age 65 and over (2016)	0.296***
	(0.0877)
Population share, Black (2016)	-0.0908***
	(0.0216)
Population share, Female (2016)	0.0542
	(0.0687)
Population share, Hispanic (2016)	-0.125***
	(0.0199)
Population share, White non-Hispanic (2016)	0.0618***
	(0.0210)
Unemployment rate (2015-2019 avg.)	-0.102
	(0.0903)
Log mean household income (2015-2019 avg.)	-0.0309
	(0.0364)
Share with some college (2015-2019 avg.)	-0.369***
	(0.0322)
Δ Population share, Age 25-34 (2016 minus 2013)	0.181*
	(0.102)
Δ Population share, Age 35-44 (2016 minus 2013)	-0.137
	(0.206)
Δ Population share, Age 45-54 (2016 minus 2013)	-0.307
	(0.219)
Δ Population share, Age 55-64 (2016 minus 2013)	0.372*
	(0.204)
Δ Population share, Age 65 and over (2016 minus 2013)	-0.0873
	(0.172)
Δ Population share, Black (2016 minus 2013)	0.405**
	(0.156)
Δ Population share, Female (2016 minus 2013)	-0.317***
	(0.0910)
Δ Population share, Hispanic (2016 minus 2013)	0.175*
	(0.0919)
Δ Population share, White non-Hispanic (2016 minus 2013)	0.285
	(0.178)
Δ Share with some college (2015-2019 minus 2010-2014)	-0.0148
	(0.00934)
Δ Log mean household income (2015-2019 minus 2010-2014)	0.0471
	(0.0305)
Δ Unemployment rate (2015-2019 minus 2010-2014)	0.121*
	(0.0624)
Constant	0.167
	(0.145)
State FEs	Y
Observations	3,112
R-squared	0.631

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Regarding my second robustness check, I use the 2020-2016 Republican Senate vote share as my dependent variable in place of the Republican presidential vote share. All other model specifications remain the same. If US voters associate the introduction of 2018-2019 tariffs solely with the president's administration, then the 2020 Senate results will not be influenced by the channel variables. Table 5 exhibits all the coefficients for the new regression model. Again, no significant results are obtained for the tariffs' impact with p-value always greater than acceptable thresholds. However, it is important to note that this effect is found with a different sample of only 1,249 counties as opposed to 3,112. The coefficients for import protection, retaliation and input cost variables do not provide any startling evidence that could undermine the validity of my main findings. They may show that an incumbent president's actions have limited ramifications for his or her party's election outcomes.

Table 5. Regression results for the relationship between the difference in the 2020-2016 Republican Senate vote share and the values of import protection, foreign retaliation, and rising input costs with control variables

VARIABLES	(1) Δ Republican Senate Vote Share (2020 minus 2016)
Import Protection	-0.340
	(0.395)
Foreign Retaliation	2.732
	(2.387)
Rising Input Costs	-1.143
	(1.084)
Republican Presidential Vote Share (2016)	-0.00649
	(0.0763)
Δ Republican Presidential Vote Share (2016 minus 2012)	0.0296
	(0.205)
Covid Incidence	-4.70e-05
	(3.13e-05)
Population share, Age 25-34 (2016)	0.259**
	(0.120)
Population share, Age 35-44 (2016)	0.612**
	(0.242)
Population share, Age 45-54 (2016)	0.148
	(0.251)
Population share, Age 55-64 (2016)	0.215
	(0.232)
Population share, Age 65 and over (2016)	0.224
	(0.147)
Population share, Black (2016)	-0.0394
	(0.0555)
Population share, Female (2016)	-0.117
	(0.130)
Population share, Hispanic (2016)	0.0300
	(0.0669)
Population share, White non-Hispanic (2016)	0.0802
	(0.0679)
Unemployment rate (2015-2019 avg.)	0.668*
	(0.345)
Log mean household income (2015-2019 avg.)	-0.196*
	(0.103)
Share with some college (2015-2019 avg.)	-0.127
	(0.104)
Δ Population share, Age 25-34 (2016 minus 2013)	0.0992
	(0.293)
Δ Population share, Age 35-44 (2016 minus 2013)	0.588
	(0.393)
Δ Population share, Age 45-54 (2016 minus 2013)	0.287
	(0.290)
Δ Population share, Age 55-64 (2016 minus 2013)	-0.325
	(0.320)
Δ Population share, Age 65 and over (2016 minus 2013)	0.330
	(0.315)
Δ Population share, Black (2016 minus 2013)	-0.0203
	(0.138)
Δ Population share, Female (2016 minus 2013)	0.314
	(0.207)

Δ Population share, Hispanic (2016 minus 2013)	-0.303**
	(0.109)
Δ Population share, White non-Hispanic (2016 minus 2013)	-0.0763
	(0.126)
Δ Share with some college (2015-2019 minus 2010-2014)	0.0154
	(0.0239)
Δ Log mean household income (2015-2019 minus 2010-2014)	0.147
	(0.0963)
Δ Unemployment rate (2015-2019 minus 2010-2014)	-0.240
	(0.203)
Constant	0.762
	(0.515)
State FEs	Y
Observations	1,249
R-squared	0.315

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

For my final robustness analysis, I eliminate outliers from the sample. This ensures that my results are not disrupted by the presence of extreme values. I exclude observations with the highest and lowest vote share shifts between 2020 and 2016. It is where the dependent variable is below the 5th percentile, the value of -0.0179165, or above the 95th percentile, the value of 0.0589435. New results are presented in Table 6, with the remaining 2,801 observations in the sample. The coefficient for rising input costs does not differ greatly from its counterpart from Table 3 and is still insignificant. However, the estimate for import protection is now statistically insignificant, in contrast to the full sample estimate. Then, it is likely that the original sample contains influential outliers, so that the regression estimate is to a great extent affected by such an outlier. This evidence raises concerns about the validity of the determined impact for import protection. Coefficient for foreign retaliation remains statistically significant, but now even at the 5% level ($p < 0.05$). Again, higher exposure to foreign retaliation by county's industries leads to relatively more votes in favor of Republican candidate. A one standard deviation increase in industries' exposure to foreign retaliation is associated with a growth in the vote share equal to $0.574 \times 0.0013436 \approx 0.7$ percentage points. The magnitude of this effect relative to the new sample's mean of vote share is not very strong with the value of only 4.5% ($0.00077123/0.0170224 \approx 4.5\%$) and comparable to the main estimate's magnitude of 5.7%. The increase in statistical significance may occur because of decreased variability in the dataset caused by the exclusion of outliers. Therefore, given estimation does not undermine my baseline results.

Table 6. Regression results for the relationship between the difference in the 2020-2016 Republican Presidential vote share and the values of import protection, foreign retaliation, and rising input costs with control variables using sample without outliers

VARIABLES	(1) Δ Republican Presidential Vote Share (2020 minus 2016)
Import Protection	-0.0426
	(0.0411)
Foreign Retaliation	0.574**
	(0.256)
Rising Input Costs	-0.0388
	(0.128)
Republican Presidential Vote Share (2016)	-0.0374***
	(0.00566)
Δ Republican Presidential Vote Share (2016 minus 2012)	0.0958***
	(0.0197)
Covid Incidence	1.33e-06
	(3.60e-06)
Population share, Age 25-34 (2016)	-0.118***
	(0.0289)
Population share, Age 35-44 (2016)	-0.0809**
	(0.0359)
Population share, Age 45-54 (2016)	-0.0821**
	(0.0372)
Population share, Age 55-64 (2016)	-0.0103
	(0.0317)
Population share, Age 65 and over (2016)	-0.0111
	(0.0184)
Population share, Black (2016)	-0.0275*
	(0.0142)
Population share, Female (2016)	-0.0960***
	(0.0162)
Population share, Hispanic (2016)	0.0148**
	(0.00714)
Population share, White non-Hispanic (2016)	-0.000882
	(0.0158)
Unemployment rate (2015-2019 avg.)	-0.119***
	(0.0364)
Log mean household income (2015-2019 avg.)	0.0106
	(0.00984)
Share with some college (2015-2019 avg.)	-0.0942***
	(0.0116)
Δ Population share, Age 25-34 (2016 minus 2013)	0.0987***
	(0.0341)
Δ Population share, Age 35-44 (2016 minus 2013)	0.198***
	(0.0523)
Δ Population share, Age 45-54 (2016 minus 2013)	0.0574
	(0.0507)
Δ Population share, Age 55-64 (2016 minus 2013)	0.0114
	(0.0561)
Δ Population share, Age 65 and over (2016 minus 2013)	-0.0852**
	(0.0333)
Δ Population share, Black (2016 minus 2013)	-0.0758*
	(0.0383)
Δ Population share, Female (2016 minus 2013)	0.0843**
	(0.0383)
Δ Population share, Hispanic (2016 minus 2013)	-0.0753*
	(0.0416)
Δ Population share, White non-Hispanic (2016 minus 2013)	-0.0174
	(0.0160)
Δ Share with some college (2015-2019 minus 2010-2014)	0.00745**
	(0.00294)
Δ Log mean household income (2015-2019 minus 2010-2014)	0.00528
	(0.0107)

Δ Unemployment rate (2015-2019 minus 2010-2014)	0.0331**
	(0.0156)
Constant	0.102**
	(0.0506)
State FEs	Y
Observations	2,801
R-squared	0.368

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6. Discussion

In this part, I will elaborate on the practical implications of the results. The 2018-2019 tariffs introduced during President Trump's tenure have been proven to have a significant, albeit weak effect on the presidential election results in 2020 through two channels; import production and foreign retaliation. There is not enough evidence to ascertain any association between rising input costs and the change in the vote share. Additional checks partially supported the validity of these findings.

The association between increased import protection for county's industries and support for Donald Trump in the 2020 Presidential elections remains negative. This result is surprising and contradicts Flaaen, Hortacsu and Tintelnot (2019), who demonstrated that the imposition of safeguard measures on washing machines lead to positive impacts on the local economy. According to economic theory, more trade barriers should boost domestic output by restricting the number of imported goods or increasing their price vis-à-vis local products. Consequently, more workforces may be required to sustain the demand, leading to higher employment in the county and higher support for politicians. Nevertheless, the relationship may be in accordance with studies conducted by Che et al. (2016) and Autor et al. (2020), who show that trade exposure is intertwined with the choice of more radical and protectionist candidates. Trade restrictive measures reduce counties' exposure to trade competition and could have caused a decline in the support of a more radical candidate, assuming President Trump was regarded as one. Some of his supporters may have decided to vote for other candidates, which emphasize different political objectives after this trade policy demand was fulfilled during Trump's tenure between 2017-2021. Blanchard et al. (2019) support this conclusion by stating that protection did not lead to vote gains during congressional elections in 2018. It is worth mentioning that one of the robustness tests with a different sample demonstrated that this estimate is dubious. Its statistical significance was lost when the values above 95^{th} and below 5^{th} percentile were excluded. Hence, a degree of caution is appropriate in interpreting this outcome.

Obtained results demonstrated that higher exposure to foreign retaliation has a positive significant influence on the growth in the Republican party vote share. This link has been identified with a full sample and without outliers, consequently supporting its plausibility. This result appears to be counterintuitive since the retaliatory measures should lead to a decline in the sales of U.S. goods in overseas markets. It contradicts some of the previous outcomes, which argue that countermeasures resulted in job losses (Waugh, 2019) and electoral losses for the Republican party (Blanchard et al., 2019; Chyzh, & Urbatsch, 2019). As there is no economic justification for this estimate, it may suffer from omitted variable bias. In my research, I do not account for the effect of agricultural subsidies and the Trade Adjustment Assistance (TAA) program for workers. In fact, these may be particularly prominent in areas harmed the most by retaliatory tariffs, so that there is a positive correlation between these two variables. Choi and Lim (2021) conclude that agricultural subsidies outweighed Chinese retaliatory tariffs, resulting in a Republican vote share rise in the 2020 election. This effect is particularly striking in the Republican majority states, hence in regions mostly targeted by retaliatory measures (Fajgelbaum et al., 2020; Fetzer, & Schwarz, 2021). Furthermore, it is easier to introduce policies, which counterbalance the negative impacts of retaliatory measures than the consequences of increasing costs as there the global supply chain is more complex.

According to the literature, the 2018-2019 tariffs adversely affected input costs and had a considerable impact on economic outcomes. Handley et al. (2020) emphasized the role of intermediate input in the decreasing export growth for the United States, so hindered competitiveness of producers. While Cavallo, et al. (2019) argued that higher input costs led American firms to pursue reduced profit margins. Flaaen & Pierce (2019) found that Donald Trump's trade barriers caused decline in a manufacturing employment and relative increases in producer prices. However, no evidence was found that these economic implications for rising costs were transformed into political repercussions for the incumbent president. Some of the focus of my analysis was on the supply side, with input costs having a direct impact on producers, and then on employment and prices as a result. Therefore, it could be that the negative consequences of higher input prices are limited or concern a small proportion of voters. As noted by Cavallo et al. (2019), there is no explicit indication that the final prices for consumers were negatively influenced. The lack of meaningful results can also be explained by the assumption I used to construct my sample. If a certain industry is not ranked among the top ten industries affected, the effect is then equal to 0. As a result, some important information is unintentionally omitted, which makes it more difficult to detect any impact.

7. Conclusion

To conclude, my research attempted to address the question of the impact of Donald Trump's Trade War between 2018-2019 on the 2020 United States presidential elections through the channels of import protection retaliation, and intermediate input costs. For my analysis, I used the state fixed effects regression model with controls for covid incidence, socioeconomic and demographic factors, and pre-election trends. With the baseline specification, I found two statistically significant estimates. Firstly, there exists a negative association between more import protection and the relative support for the Republican party candidate. A one standard deviation higher import protection causes 0.07 percentage points decline in the Republican vote share. Presumably, this relationship is a consequence of a decline in the perceived trade exposure and support for radical candidates. Secondly, in counties more exposed to retaliatory tariffs, the association between foreign countermeasures and election outcome for Republicans was estimated to be positive. A one standard deviation increase in foreign retaliation exposure in a county is associated with an increase in the vote of 0.1 percentage points. This unexpected finding can be explained by the introduction of counterbalancing policies, such as agricultural subsidies, which likely correlate with the retaliatory measures and may outweigh the negative effects. Lastly, there is no evidence that rising input costs had a political impact for election results. This can occur if higher input prices have a limited effect on voting decisions or due to insufficient data. All effects were calculated to be of negligible magnitude. Disregarding the import protection channel, robustness checks did not provide any signals that could undermine the validity of my results. Therefore, Donald Trump's Trade War between 2018 to 2019 is proven to have a heterogeneous, albeit minor political impact through import protection and foreign retaliation channel on the 2020 US presidential election outcome.

My study to some extent confirms previous empirical findings (e.g., Autor et al., 2020; Che et al., 2016; Blanchard et al., 2019), which demonstrate that trade policies have a range of consequences for domestic politics. Although, their influence is quite modest and varies for each channel. While proposing new trade law, policymakers should recognize that the relationship between gains and losses stemming from tariffs and their chances of re-election is very complex. So that higher protection does not guarantee an increased support, and conversely for retaliation and input costs.

As mentioned, the prime limitation of the study is the lack of sufficient data on the effect of import protection, retaliation, and input costs. Once more data is published, further research may attempt to estimate more detailed county-level values for all industries. This new sample can deliver more accurate estimates for tariffs impact variables. Further impediment of this analysis is that the coefficient for the impact of foreign retaliation may be upward-biased. Hence, my findings should be tested with an adjusted model, which controls for the effect of agricultural subsidies, the Trade Adjustment Assistance program or even tariff exclusions. Due to a lack of this type of data on a county level, it was not viable in my analysis. Lastly, I evaluated the impact of President Trump's trade policy between the year 2018 to 2019. However, voters are likely to consider the entire four-year tenure when deciding who to cast their vote for. There were no major shifts in US trade policy in 2017, so this is not a cause for concern. Nonetheless, significant changes occurred after 2019. Further research may be conducted to consider this long-term perspective and extend the studied period beyond 2019 by using updated values for each of the three channels from 2018 to 2020.

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