Counterfactual Retaliatory Tariffs and the 2020 United States Presidential Election*

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We provide a statistical framework to study the impact of counterfactual retaliatory tariffs on the 2020 United States Presidential Election. Using reduced-form estimates similar to Lake and Nie (2023) and the institutional features of the US election, we predict the national election outcome as a weighed average of the state-level outcomes. We also formulate an "optimal tariff" problem in which a government seeks tariffs that generate maximum impact on the election outcomes in another country subject to linear constraints. We provide the full analytical solution to the problem and implement it using trade statistics before the trade war and the reduced-form estimates. We find that the optimal tariffs can flip the outcome in certain states compared to the current tariffs.

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1 Introduction

Ever since the beginning of the US-China Trade War, researchers, policymakers and commentators have been wondering about the impact of the Chinese retaliatory tariffs on the United States, especially on people's voting patterns. Several papers have documented that the retaliatory tariffs reduce voters' support for the Republican candidates in the 2018 midterm election and the 2020 presidential election (Blanchard et al., 2019; Lake and Nie, 2023). However, it is also clear that the retaliatory tariffs largely fall on counties where the majority of voters supported Donald Trump in the 2016 presidential election (Fajgelbaum et al., 2020). In this paper, we provide a statistical framework to predict counterfactual election outcomes assuming a different tariff scheme imposed by the Chinese government. We ask whether the Chinese retaliatory tariffs can be engineered to have a larger impact on the US election.

Our approach of predicting counterfactual election outcomes is as follows. We first follow Lake and Nie (2023) and estimate the impact of the county-level retaliatory tariff shocks on the change in Republican voting shares from 2016 to 2020. We then assume that such effects can be extrapolated (linearly) when China adopts an alternative tariff scheme. This requires us to construct the counterfactual county-level shocks using the new tariff scheme and use these shocks as independent variables to predict the changes in Republican voting shares in each county. Given baseline Republican voting shares, we can predict the shares in the 2020 election and aggregate them to the state level and determine the winner of each state. We then obtain the electoral college (EC) votes won by each candidate and predict the final election outcome.

In our analysis, the choice of baseline Republican voting shares is crucial for the predicted outcomes under various tariff schemes. For example, if we allow all the other observable and unobservable factors, such as Trump's protective tariffs, agricultural subsidies and the expansion of health insurance coverage, to affect the voting outcomes, the baseline Republican voting shares in the swing states will be so low that even a 100% Chinese tariff on all US exports will not alter any states' outcomes. In contrast, if we start from the 2016 election, take into account the US protective tariffs and ignore the non-tariff factors, Chinese tariffs can change the swing states' outcomes at much lower tariff rates. Therefore, we designed three counterfactual scenarios, corresponding to different

assumptions on the other factors between 2016 and 2020 that influence the 2020 election outcomes. When we consider both the US protective tariffs and the Chinese retaliatory tariffs and ignore the other non-tariff factors, we find that Michigan, Wisconsin and Pennsylvania would have flipped their 2016 election outcomes to support the Democratic candidate had China implemented a tariff of 22%, 60% and 81% on all industries, respectively. As Pennsylvania flips its outcome, the Republican would have lost the nationwide election. The retaliatory tariffs, however, may have a more decisive effect at lower rates if we take into account some more anti-Republican factors and start from lower baseline vote shares in these states.

We next provide a methodology to compute "optimal tariffs" that maximize their impact on the Republican voting share in a specific set of US counties. We formulate the problem as searching for industry-level tariffs that minimize the predicted aggregate Republican voting share subject to two constraints: (1) the (predicted) change in total tariff revenue by China has to be below a certain value (2) the tariff in each industry has to be below an upper bound. This is to ensure that the tariffs are in a reasonable range and that there is an opportunity cost of raising any industry's tariff. Because the predicted change in the voting share is linear in industry-level tariffs and the constraints are also linear, we eventually formulate the problem as linear programming and obtain closed-form "bang-bang" type of solutions. In particular, we find that there is an industry-level sufficient statistic that summarizes an industry's priority in getting tariffs. When industries are ranked by this statistic, industries with high values will receive a tariff at the upper bound, and those with low values will receive a zero tariff. There is a cutoff industry that may receive a tariff between zero and the upper bound, and the tariff is determined by the total tariff revenue constraint. This statistic is higher if an industry is concentrated in counties with a higher voter-to-workforce ratio, and the pre-trade-war exports of the industry is irrelevant in determining this statistic.

We implement this solution using the same data as we estimate the impact of the current tariffs. The priorities of industries to get tariffs depend on for which set of counties we want to maximize the impact of tariffs. When minimizing the nationwide Republican voting share subject to the current predicted tariff revenues, we find that 15 out of 27 industries receive positive tariffs. Manufacturing of Automobiles (NAICS 336) and Manufacturing of Machinery (NAICS 333) are two of the largest exporting sectors with positive tariffs. However, larger exporting sectors such as Manufacturing of

Chemicals (NAICS 325), Manufacturing of Equipment (334) and Crop Production (111) have low priority and should have zero tariffs under optimality. Depending on the set of counties to influence, we find the optimal retaliatory tariffs amplify the impact of the current retaliatory tariffs by 5 to 21%. Aggregated to state-level outcomes, the optimal tariffs would make Michigan voters support the Democratic candidate while the current tariffs cannot.

This study contributes to two strands of literature. The first strand of literature is on the US-China trade war, especially its corresponding tariff shock on US elections. Many scholars have studied the economic impact of the trade war, including its implications on welfare (Amiti et al., 2020; Fajgelbaum et al., 2020), global production relocation (Fajgelbaum et al., 2021), consumption (Waugh, 2019) and firm-level outcomes (Jiao et al., 2022; Sheng et al., 2023). Several papers examine the political consequences of the trade war (Blanchard et al., 2019; Li et al., 2020; Lake and Nie, 2023).[1] Blanchard et al. (2019) (henceforth BBC) construct the Bartik-style tariff shock and conclude that the retaliation impact account for one-quarter of the 2018 midterm election Republican vote decline. Lake and Nie (2023) (henceforth L&N) analyze the effect of trade war tariff shock on the 2020 presidential election. Nevertheless, current literature evaluates the effect of the actual tariffs, while our paper focuses on the counterfactual political outcomes due to hypothetical tariff schemes.

The second strand of literature is about optimal tariffs. The literature discusses political motives, trade protection, and the optimal trade policy, back to Grossman and Helpman (1995), Goldberg and Maggi (1999), and more recent studies, such as Broda et al. (2008) and Blanchard et al. (2016). We provide a different concept of "optimal tariffs": tariffs that generate maximum effects on political outcomes in other countries given certain constraints (tariffs not being too large). We provide a full analytical characterization of such tariffs and quantify these tariffs in the context of the US-China trade war.

This paper structures as the following: Section 2 replicates the results in Lake and Nie (2023) using Bartik-like measures constructed by ourselves. Section 3 discusses how we predict the counterfactual tariffs and gauge the potential impact of tariffs on voting outcomes using simple uniform tariffs. Section 4 formulates the optimal tariff problem mathematically, provides an analytical solu-

[1] More generally, our research is related to papers that study the relationship between trade and election outcomes, including Margalit (2011), Conconi et al. (2014), Lake and Millimet (2016), Jensen et al. (2017), Colantone and Stanig (2018), Autor et al. (2020), and Che et al. (2022).

tion, and implements the solution using the trade statistics and reduced-form estimates obtained in Section 2. We conclude in Section 5.

2 The Impact of Current Retaliatory Tariffs on Votes

In this section, we study the impact of the current retaliatory tariffs on the Republican voting shares. Our data and methods follow Blanchard et al. (2019) and Lake and Nie (2023) closely.

We draw data on tariffs, county-level characteristics and voting outcomes from several sources. We use the 2017 trade data and the retaliatory tariff data compiled by Bown (2019). In 2017, the US exported 143 billion dollars of goods to China.[2] After three waves of Chinese tariffs, the current retaliation tariffs range from 5% to 35% and are levied on 5727 out of the 5922 HS 8-digit products that China imports from the United States in 2017. The tariffs are equivalent to a 15.08% uniform tariffs on all products, and China would collect a 21,583 million dollar worth of tariff revenue had the trade volumes kept the same as the 2017 levels.

We construct Bartik-style tariff shocks (TS) due to Chinese retaliatory tariffs for each county n as in Blanchard et al. (2019):

$$TS_n^r = \sum_{k \in \mathcal{K}} \frac{L_{nk} X_k t_k^r}{\bar{L}_n L_k}, \tag{1}$$

where k denotes an industry that belongs to the set of all industries, $\mathcal{K}$.[3] TS_n^r denotes the tariff shock of Chinese retaliation. X_k denotes the US export value to China in industry k in 2017. t_k^r is the retaliation tariff imposed on the US export. L_{nk} stands for the employment in industry k, county n, which we obtain from the County Business Patterns Database compiled by Eckert et al. (2020). L_k is the total employment in industry k across all counties in our sample. Finally, $\bar{L}_n$ is the total workforce size in county n, proxied for by the population aged 15-64 in 2016 obtained from the US Census Bureau Annual County Residential Population Estimates Data.[4] In addition, we define similar county-level tariff shocks due to the Trump tariffs, $TS_n^{us} = \sum_{k \in \mathcal{K}} \frac{L_{nk} I_k t_k^{us}}{\bar{L}_n L_k}$, where I_k is the

[2] According to Bown's data, the total export from the US to China was 149 billion dollars in 2017. However, only 143 billion goods can be matched to the NAICS industries. We focus on the latter set of goods in our analysis.

[3] In our analysis, we include 88 three-digit NAICS industries, among which 27 produce tradable goods.

[4] In contrast, Lake and Nie (2023) use the total employment, $\sum_k L_{nk}$ as a proxy for $\bar{L}_n$. We prefer the measure in Blanchard et al. (2019) because it better reflects the tariff shocks on an average resident in the county, and $\bar{L}_n$ is also closer to the total number of voters.

total US imports in industry k and t_k^{us}. We use it as a control variable in our regressions.

The outcome variable of interest is the change of Republican voting shares in each county from 2016 to 2020, as in Lake and Nie (2023). They collect county-level voting data in 2012, 2016 and 2020 from David Leip's Election Atlas (version 0.9), and define the Republican voting share as the share of Republican votes in total votes that support either Republican or Democratic candidates.[5] They also use a rich set of county-level characteristics as control variables in their analysis. We borrow these data from their replication package. Our final dataset contains 3110 counties in 49 states.[6]

Our regression specification follows Lake and Nie (2023):

$$\Delta V_n = \beta^{us} TS_n^{us} + \beta^r TS_n^r + \gamma Z_n + \epsilon_n, \tag{2}$$

where ΔV_n is the change in Republican voting share in county n from 2016 to 2020, Z_n represents a rich set of control variables, and ϵ_n is the error term. As discussed in Lake and Nie (2023), this specification is under the threat of omitted variables. Following their approach, we control for agricultural subsidies from the Market Facilitation Program in 2018 and the change in Republican voting shares from 2012 to 2016. The latter control aims to remove long-term trends in county-level voting behavior and to limit the omitted variable problem. Beyond these two variables, we also add state-level fixed effects and 67 additional controls as in Lake and Nie (2023), including the level and changes in income, employment, share of population of difference races, educational levels, age groups, etc.[7] We present summary statistics of the dependent and key independent variables in Appendix Table A.1.

We show the estimation results of regression (2) in Column (1) of Table 1. Similar to the results in Lake and Nie (2023), we find that the county-level retaliatory tariff shocks significantly reduced the Republican voting shares. Taking the estimated coefficient in Column 1 (-0.973), a one-standard

[5]The share of votes supporting third parties is small. We follow Lake and Nie (2023) and ignore these votes in our analysis.

[6]We exclude Alaska following Lake and Nie (2023) because the state does not report county-level votes. We exclude the District of Columbia from our analysis to be consistent with the sample in Blanchard et al. (2019). They each hold three electoral college votes, and neither of them are swing states (with a margin smaller than 10%). Therefore, we expect that ignoring them will not affect our main result.

[7]Lake and Nie (2023) also adopt a heteroscedasticity-based instrumental variable approach to address the omitted variable problem (Lewbel, 2012). They conclude that this method deliver similar results as controlling for a rich set of county-level characteristics and state-level fixed effects. Therefore, we only adopt the latter method in our paper.

deviation increase in the retaliation shock TS_n^r (0.332) will reduce the Republican vote share by 0.973×0.332 = 0.32%, compared to an average decline of 0.55% in Republican vote share across all counties and a one standard deviation of the change in Republican vote share of 2.58%. Consistent with the literature, we also find that the Trump tariffs and the agriculture subsidies help to increase the Republican vote shares.

We construct the county-level retaliatory tariff shocks following the method in Blanchard et al. (2019). Though our measure is highly correlated with the one provided in their replication package (with a correlation coefficient of 0.96), the two measures are not exactly the same. In Column (2) of Table 1, we use their measure instead of the one constructed by ourselves. The estimates are similar. We conduct another robustness check in Column (3) using Lake and Nie's tariff shocks. As discussed in footnote 4, they use total employment for the denominator $\bar{L}_n$ instead of total workforce. Since the former is smaller than the latter, their shock measures are larger than ours and the one used by Blanchard et al. (2019), and it is not surprising that we obtain smaller coefficients for the retaliation tariff shock and the US tariff shock. However, both coefficients are significant with expected signs. In our quantitative analysis, we use the benchmark estimates in Column (1). We provide robustness checks using the estimates in Column (3) in the Appendix.

In the above analysis, we do not allow the treatment effects to vary by county characteristics. In Appendix A, we show that the impact of the retaliation tariff shocks is larger in "deep blue" states than in "deep red" and swing states. Though the differences are not statistically significant, our counterfactual framework allows us to incorporate such heterogeneous treatment effects and we discuss such counterfactuals in Appendix B.1.

3 The Impact under Counterfactual Tariffs

This section discusses our counterfactual analysis in detail. We first present a uniform tariff scheme considering the three scenarios; next, we discuss the result of the counterfactual uniform tariff scheme.

Table 1: Main Regression Replication

	(1)	(2)	(3)
Retaliation shock	-0.973***		
	(0.313)		
Retaliation shock (BBC)		-1.197***	
		(0.392)	
Retaliation shock (L&N)			-0.246**
			(0.120)
US tariff shock (BBC)	0.373**	0.456**	
	(0.163)	(0.173)	
US tariff shock (L&N)			0.183***
			(0.050)
Δ lagged Rep vote share	0.211***	0.213***	0.213***
	(0.033)	(0.033)	(0.033)
Agriculture subsidy	0.394***	0.404***	0.404***
	(0.129)	(0.129)	(0.132)
Controls	Yes	Yes	Yes
R-sqr	0.852	0.852	0.852
Obs	3110	3110	3110

Notes: The dependent variable is the change in the Republican voting share from 2016 to 2020. The key independent variable, "Retaliation Shock", is constructed as in equation (1). Variables followed by "BBC" are obtained from the replication materials of Blanchard et al. (2019) and those followed by "L&N" are obtained from the replication materials of Lake and Nie (2023). Robust standard errors clustered at the state level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.1 Predicting Counterfactual Voting Outcomes

In this section, we discuss how we predict voting outcomes under counterfactual retaliatory tariff schemes, $t_k^{r,cf}$, $k \in \mathcal{K}$. We first calculate the counterfactual tariff shocks at the county level following equation (1) by replacing the actual retaliatory tariffs t_k^r with $t_k^{r,cf}$. We denote the counterfactual county-level tariff shocks with $TS_n^{r,cf}$. Denoting the estimated coefficients and the residual term in regression (2) with "hats", we have the following identity:

$$\Delta V_n = \hat{\beta}^{us} TS_n^{us} + \hat{\beta}^r TS_n^r + \hat{\gamma} Z_n + \hat{\epsilon}_n. \tag{3}$$

By construction, the share of county n voters who support Trump in 2020 can be written as $V_n^{2020} = V_n^{2016} + \Delta V_n$. However, to compute the counterfactual change ΔV_n^{cf} and the corresponding counterfactual voting outcomes in 2020, $V_n^{2020,cf} \equiv V_n^{2016} + \Delta V_n^{cf}$, we not only need to replace TS_n^r with $TS_n^{r,cf}$, but also need to take a stand on the other terms, i.e., $\hat{\beta}^{us} TS_n^{us}$, $\hat{\gamma} Z_n$ and $\hat{\epsilon}_n$. We consider

three different scenarios, denoted by superscripts $cf1, cf2$ and $cf3$, respectively. In the first scenario, we keep all three terms $\hat{\beta}^{us}TS_n^{us}$, $\hat{\gamma}Z_n$ and $\hat{\epsilon}_n$ and predict the change in vote shares as

$$\Delta V_n^{cf,1} = \hat{\beta}^{us}TS_n^{us} + \hat{\beta}^{r}TS_n^{r,cf} + \hat{\gamma}Z_n + \hat{\epsilon}_n = \Delta V_n + \hat{\beta}^{r}(TS_n^{r,cf} - TS_n^{r}).$$

Therefore, $\Delta V_n^{cf,1}$ takes into account the actual US tariff protections as well as other observed (Z_n) and unobserved factors ($\hat{\epsilon}_n$) that have changed from 2016 to 2020. In the second scenario, we ignore the other observed and unobserved factors and but allow for both the US tariffs and the counterfactual Chinese tariffs, i.e., $\Delta V_n^{cf,2} = \hat{\beta}^{us}TS_n^{us} + \hat{\beta}^{r}TS_n^{r,cf}$. This scenario is interesting since the Chinese government might not know the other factors at the time of the retaliatory tariffs. Finally, we consider a third scenario in which the Chinese government imposes unilateral tariffs. In this case, the change in vote shares only depend on the Chinese tariffs, i.e., $\Delta V_n^{cf,3} = \hat{\beta}^{r}TS_n^{r,cf}$.

With the predicted changes in vote shares, $V_n^{cf,i}, i = 1, 2, 3$, we can predict state and nationwide election outcomes. The share of voters supporting Trump in state s, can be written as

$$V_s^{cf,i} = \sum_{n \in \mathcal{N}_f} \left(V_n^{2016} + \Delta V_n^{cf,i}\right) \omega_n, \tag{4}$$

where $\mathcal{N}_f$ is the set of counties in state s and ω_n is the share of Democratic and Republican voters of county n within the state in 2016. The nationwide election outcome depends on the result in each state and the electoral votes won by the candidates. We predict the electoral votes won by Donald Trump by

$$V^{cf,i} = \sum_{s \in \mathcal{S}} ec_s \times \mathbb{1}\left(V_s^{cf,i} > 0.5\right),$$

where ec_s denotes the number of electors allocated to state s according to the Electoral College (EC) system. Since a candidate wins a presidential election with at least 270 electoral college votes, Mr. Trump would won the 2020 election if $V^{cf,i} \geq 270$.

We now discuss two key assumptions behind our counterfactuals. First, the reduced-form analysis only reveals how voters' behavior in a county with a larger tariff shock compared to a county with a smaller tariff shock. The common effect of the retaliatory tariffs across all locations is captured by the constants, which we assume not changing in counterfactual 1 and ignore in counterfactuals 2 and

3. In typical reduced-form analysis such as Autor et al. (2013), researchers ignore the common effect and use the estimated coefficients and observed shocks to calculate aggregate effects. We follow the same tradition here.[8] Second, we assume the impact of tariff shock, β^r, does not change when we change the underlying tariffs. This approximation can work well when the counterfactual shock $TS_n^{r,cf}$ is close to the actual one, but may not be precise enough if the impact of the shock is non-linear and the counterfactual tariffs are far from the current ones.

To sum up, we design three different ways to predict the voting outcomes under counterfactual Chinese tariffs. In the following sections, we use the formulas developed above to assess the impact of different tariff schemes and search for retaliatory tariffs that have maximal impact on the voting outcomes.

3.2 A Simple Uniform Tariff

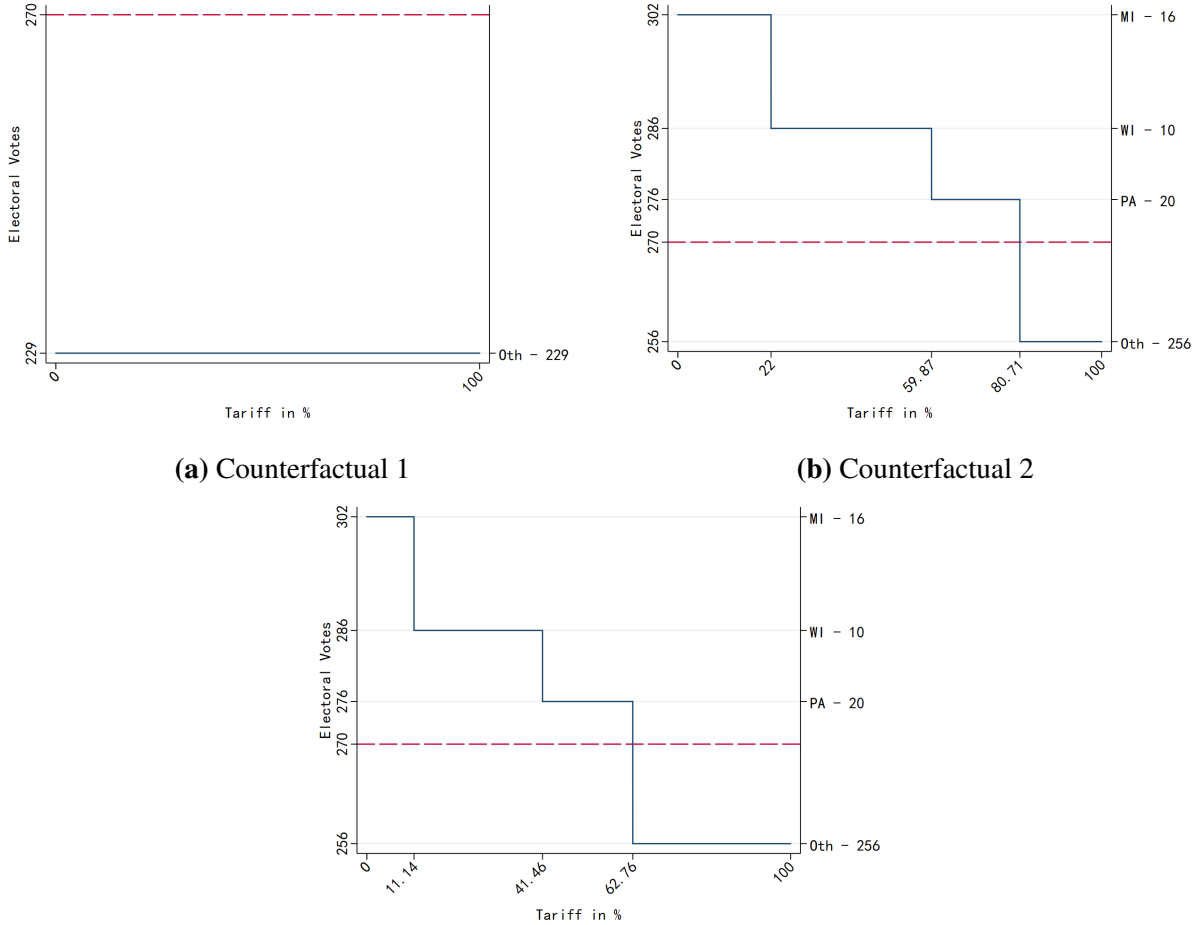
In this section, we consider a simple uniform retaliatory tariff across all products imposed by China, i.e., $t_k^r = t^r, \forall k \in \mathcal{K}$. Therefore, China is not strategically choosing its tariffs to punish the US consumers or politicians. The purpose is to assess the level of tariffs needed to make a significant impact on the US 2020 Presidential Election.

From the definition of the county-level tariff shock, equation (1), it is clear that TS_n^r strictly increases with the uniform tariff t^r for all n. It follows that the county-level counterfactual Republican voting shares strictly decreases with t^r because $\hat{\beta}^r$ is negative. The nationwide Republican electoral votes, $V^{cf,i}$, weakly decrease with t^r. For small changes in t^r, it is possible that $V^{cf,i}$ does not change because none of the states are swing states and small changes in state-level voting shares do not alter the state-level results, i.e, $\mathbb{1}\left(V_s^{cf,i} > 0.5\right)$.

In Figure 1, we plot the predicted EC votes won by Donald Trump under different levels of uniform retaliatory tariffs by China. We experiment with tariffs ranging from 0 to 100%. The three panels correspond to counterfactuals 1, 2 and 3, respectively. Panel 1(a) shows the counterfactual EC votes allowing all the other factors to have affected the election outcomes. The flat line at the number

[8] Another approach is to use a structural model to infer the "common effect" which arises from spillovers and general equilibrium effects, whether disciplined by the reduced-form estimates or not. (see, for example, Caliendo et al. (2019) and Adão et al. (2022)) However, the literature has focused on the connection between trade shocks and the labor market for which researchers can apply a standard demand-supply framework. We are not aware of any standard quantitative models connecting trade shocks to political preferences, even one with labor market outcomes as the sole mediator.

Figure 1: The Impact of Uniform Retaliatory Tariffs



(a) Counterfactual 1

(b) Counterfactual 2

(c) Counterfactual 3

Notes. We plot the predicted Electoral College (EC) votes won by Donald Trump (left y-axis) under different levels of uniform retaliatory tariffs by China (ranging from 0 to 100%). Panel (a), (b) and (c) correspond to counterfactuals 1, 2 and 3, respectively. The red dashed line denotes the minimum number of votes that Trump needs for a win (270). We illustrate the states whose results are flipped and the associated change in EC votes on the right y-axis: MI (Michigan), WI (Wisconsin) and PA (Pennsylvania).

229 means that regardless of the Chinese tariffs, the predicted votes won by Trump is 229. This is because the other factors as a whole have drove the swing states in 2016 to support Joe Biden. For the remaining states that Trump won, the margins were large and cannot be changed by the range of Chinese tariffs that we consider. We illustrate the "270 to win" threshold using a red dashed line, which is way above 229. In sum, the Republicans lose the election regardless of the level of Chinese tariffs in this counterfactual.

Panel 1(b) presents a more interesting case in which we consider the impact of Chinese tariffs ignoring the other factors between 2016 and 2020 except for the US tariffs against China. It is relevant for policy makers because the Chinese retaliatory tariffs were designed during the US-China

trade war in 2018, and it was unclear how some factors, such as Trump's attempts to removal the Affordable Care Act, would impact the 2020 election results. Therefore, we start from the 2016 election results, allowing the Trump tariffs to raise the support to the Republican candidate. However, the Trump tariffs are too small to flip any swing states that voted for Hilary Clinton in 2016. When Chinese tariffs are low (lower than 22%), Trump still would win 302 EC votes as in 2016.[9] When Chinese tariffs surpass 22%, Michigan would be the first swing state whose election outcome is flipped, reducing the total EC votes by 16. As we further increase the tariffs to 60% and 81%, two other states, Wisconsin and Pennsylvania, would be flipped, reducing the total EC votes by 10 and 20, respectively. Admittedly, retaliatory tariffs at 81% may not be a feasible strategy because they impose high costs to the Chinese importers and consumers and can potentially cause very different responses by the US government. However, Chinese tariffs can flip the results in Michigan while kept at a reasonable level. Taking some other anti-Trump factors into account, such tariffs can be crucial for the 2020 election outcome.

Finally, we consider the third counterfactual and plots the relationship between total EC votes and Chinese tariffs in Panel 1(c). We find this counterfactual less attractive compared to the second one because it assumes that the Chinese government levies tariffs unilaterally without thinking about the US tariffs. Compared to the second counterfactual, it is easier for the Chinese tariffs to flip the swing states because they do not have to 'offset" the positive effects of the Trump tariffs. We find that the election results in Michigan, Wisconsin, and Pennsylvania will be flipped at a uniform tariff of 11%, 41% and 63%, respectively.

4 Retaliatory Tariffs with Maximum Impact

In this section, we allow Chinese tariffs t_k^r to differ across sectors $k \in \mathcal{K}$ and study how China can design a tariff scheme that maximizes its impact on the voting outcomes. We first formulate it as a linear programming problem and characterize its solution analytically. We then compute these tariffs

[9] Trump won a total of 306 EC votes in 2016. We dropped three votes in Alaska and one vote in Maine. Therefore, the base level of EC votes became 302. In the US presidential elections, the winning candidate takes all EC votes except in Maine and Nebraska. These two states adopt the congressional district method. Hilary Cliton won the majority of votes in Maine as well as the First Congressional District (three EC votes) but lost the Second Congressional District to Donald Trump (one EC vote). There was no split in Nebraska in 2016. For simplicity, we decide to ignore the congressional district method and assume both states adopt the winner-takes-all method. This does not affect our main quantitative predictions.

and compare with the uniform ones.

4.1 A Linear Programming Problem

Consider the Chinese government searching for a tariff scheme $\{t_k^r\}_{k\in\mathcal{K}}$ to minimize the Republican voting share in state s, $V_s^{cf,i}$. Note that the three counterfactuals only differ in their base support for Trump due to different assumptions on other factors. Using the definition of state-level voting shares in equation (4), minimizing $V_s^{cf,i}$ is equivalent to maximizing the voter-population-weighted tariff shocks within a state:

$$\sum_{n\in\mathcal{N}_s} \omega_n TS_n^{r,cf} = \sum_{n\in\mathcal{N}_s} \omega_n \left(\sum_{k\in\mathcal{K}} \frac{L_{nk} X_k t_k^r}{\bar{L}_n L_k} \right).$$

We need to impose some restrictions on t_k^r to prevent China from imposing unrealistically high tariffs to reduce the Republican voting shares. In particular, we assume that (1) the Chinese tariffs in any sector are bounded between 0 and B and (2) the total tariff revenue based on pre-trade-war US exports is T, i.e., $\sum_k t_k^r X_k = T$. We impose the restriction that $T < B \sum_k X_k$ so that there always exists tariff schemes $\{t_k^r\}_{k\in\mathcal{K}}$ that satisfy these two constraints. The second restriction reflects the China's "tit-for-tat" strategy in the trade war – it wants to maintain an average tariff (weighted by pre-trade-war US exports) as a response to the Trump tariffs.

Formally, we solve the following maximization problem

$$\max_{t_k^r} \sum_{n\in\mathcal{N}_s} \omega_n \left(\sum_{k\in\mathcal{K}} \frac{L_{nk} X_k t_k^r}{\bar{L}_n L_k} \right) \quad \text{s.t.} \quad \sum_k t_k^r X_k = T,\ t_k^r \in [0, B]. \tag{5}$$

This is a linear programming problem with both the objective and the constraints being linear in t_k^r. Note that there is no reason to restrict the set of counties to a particular state s. In practice, we can also consider counties in multiple states, $\cup\mathcal{N}_s$. To simplify our analysis, we define the following term

$$g_k \equiv \sum_{n\in\mathcal{N}_s} \omega_n \frac{L_{nk}}{\bar{L}_n L_k}, \tag{6}$$

and we can rewrite the objective as $\sum_k g_k X_k t_k^r$. Without loss of generality, we rank industries by g_k such that

$$g_1 < g_2 < \cdots < g_K,$$

where K is the total number of industries in $\mathcal{K}$. In practice, we do not find any two industries with identical g_k. Theoretically, if two industries have identical g_k, we can group them together and label them the same industry. We refer to g_k as the voter-population-weighted influence of per dollar of exports, which plays a crucial role in characterizing the solution.

Using Lagrangian method, we can characterize the solution to this problem in the following proposition:

Proposition 1. *There exists a cutoff industry $\bar{k} \in \mathcal{K}$, such that tariffs reach the upper bound B for industries above $\bar{k}$ and the lower bound 0 for industries below $\bar{k}$. The tariff of the cutoff industry is strictly smaller than B.*

Proof. We write the Lagrangian of the above problem as

$$L(t_1^r, \ldots, t_K^r, \lambda, \lambda_1, \ldots, \lambda_{2K}) = \sum_{k\in\mathcal{K}} g_k X_k t_k^r + \lambda \left(T - \sum_{k\in\mathcal{K}} X_k t_k^r \right) + \sum_{k\in\mathcal{K}} \lambda_k t_k^r + \sum_{k\in\mathcal{K}} \lambda_{K+k}(B - t_k^r),$$

where λ is the Lagrangian multiplier associated with the constraint $\sum_{k\in\mathcal{K}} X_k t_k^r = T$, λ_k is the multiplier associated with $t_k^r \geq 0$ and λ_{K+k} is the multiplier associated with $t_k^r \leq B$. Taking derivative with respect to t_k^r, we have

$$\frac{\partial L}{\partial t_k^r} = g_k X_k - \lambda X_k + \lambda_k - \lambda_{K+k} = 0, \forall k. \tag{7}$$

In addition, we have complementary slackness

$$\begin{aligned} &\lambda_k t_k^r = 0, && t_k^r > 0 \Rightarrow \lambda_k = 0, \\ &\lambda_{K+k}(B - t_k^r) = 0, && t_k^r < B \Rightarrow \lambda_{K+k} = 0 \end{aligned}$$

Combining complementary slackness conditions with the first order condition, we obtain

$$\begin{aligned} &t_k^r = B && \Rightarrow (g_k - \lambda) X_k = \lambda_{K+k} \geq 0 \\ &t_k^r \in (0, B) && \Rightarrow (g_k - \lambda) X_k = 0 \\ &t_k^r = 0 && \Rightarrow (g_k - \lambda) X_k = -\lambda_k \leq 0 \end{aligned}$$

Since we have an strict order $g_1 < g_2 < \dots g_K$, we must impose $t_k^r = B$ for industries with high g_k and $t_k^r = 0$ for industries with low g_k, as discussed in the proposition.

We now discuss a simple algorithm to find $\bar{k}$, which also implies the existence and uniqueness of the solution. Note that the tariff revenue constraint implies that $t_1^r < B$ and $t_K^r > 0$. Since $B\sum_{k=1}^K X_k > T$, there must exist a unique $\bar{k}$ such that

$$B\sum_{k=\bar{k}+1}^{K} X_k \leq T, \quad B\sum_{k=\bar{k}}^{K} X_k > T.$$

If $B\sum_{k=\bar{k}+1}^K X_k = T$, we have $t_{\bar{k}+1}^r = t_{\bar{k}+2}^r = \cdots = t_K^r = B$ and $t_1^r = \cdots = t_{\bar{k}}^r = 0$. If $B\sum_{k=\bar{k}+1}^K X_k < T$, we must have

$$t_{\bar{k}}^r = \frac{T - B\sum_{k=\bar{k}+1}^K X_k}{X_{\bar{k}}} \in (0, B). \tag{8}$$

Combining both cases, we have $t_{\bar{k}}^r \in [0, B)$. □

We now discuss the intuition behind this solution. From the first-order condition (7), the marginal benefit of increasing tariff t_k^r is to raise $g_k X_k$, which has two components: (1) voter-population-weighted influence of per dollar of exports, g_k and (2) total US exports before the trade war, X_k. However, the second term also shows up in the tariff revenue constraint and scales up the "cost" of raising tariff t_k^r. Therefore, the "pecking order" of invoking tariffs does not involve comparing the total value of exports across industries, when the goal of the policy maker is to maximize the impact of tariffs on voting outcomes.

To understand why certain industries have higher g_k than the others, we rewrite equation (6) as

$$g_k = \frac{L_{s,k}}{L_k}\sum_{n\in\mathcal{N}_s}\frac{\omega_n}{\bar{L}_n}\frac{L_{nk}}{L_{s,k}} = \frac{1}{\sum_{n\in\mathcal{N}_s} P_n} \times \frac{L_{s,k}}{L_k}\sum_{n\in\mathcal{N}_s}\frac{P_n}{\bar{L}_n}\frac{L_{nk}}{L_{s,k}}, \tag{9}$$

where the first equality is derived by dividing and multiplying the expression by state-level employment in industry k, $L_{s,k} \equiv \sum_{n\in\mathcal{N}_s} L_{nk}$, and the second equality is derived by explicitly expressing the voter share with the number of voters in each county, P_n: $\omega_n = \frac{P_n}{\sum_{n\in\mathcal{N}_s} P_n}$. Note that the total number of voters, $\sum_{n\in\mathcal{N}_s} P_n$, is the same across counties within a state, so it is irrelevant when we

maximize the political impact of the tariffs for a particular state. An industry that is concentrated in a particular state, i.e., with high $\frac{L_{s,k}}{L_k}$, has priority in receiving the retaliatory tariffs. Finally, the last term, $\sum_{n\in\mathcal{N}_s}\frac{P_n}{\bar{L}_n}\frac{L_{nk}}{L_{s,k}}$, implies that industries that distributed in counties with high voter-to-workforce ratio, should have priority in receiving tariffs. To see this, suppose all counties have the same voter-to-workforce ratio, i.e., $P_n/\bar{L}_n = p_s, \forall n \in \mathcal{N}_s$. The last term can be simplified as

$$\sum_{n\in\mathcal{N}_s}\frac{P_n}{\bar{L}_n}\frac{L_{nk}}{L_{s,k}} = p_s\sum_{n\in\mathcal{N}_s}\frac{L_{nk}}{L_{s,k}} = p_s,$$

which is irrelevant for understanding the pecking order across industries.

To further illustrate the importance of the joint distribution of $P_n/\bar{L}_n$ and $L_{nk}/L_{s,k}$, we consider a case in which there is only one state in the United States. This also corresponds to a case in which the Electoral College is abandoned and the candidate wins if he/she has more than 50% of national votes. In this case, the term $L_{s,k}/L_k$ disappears and g_k becomes

$$g_k = \sum_{n\in\mathcal{N}}\omega_n\frac{L_{nk}}{\bar{L}_n L_k} = \frac{1}{\sum_{n\in\mathcal{N}}P_n}\times\sum_{n\in\mathcal{N}}\frac{P_n}{\bar{L}_n}\frac{L_{nk}}{L_k}. \tag{10}$$

Therefore, the distribution of employment across sectors, L_k, is irrelevant for the priority of tariffs. An industry has the highest priority if a larger fraction of the industry's employment is located in counties with higher voter-to-workforce ratios.

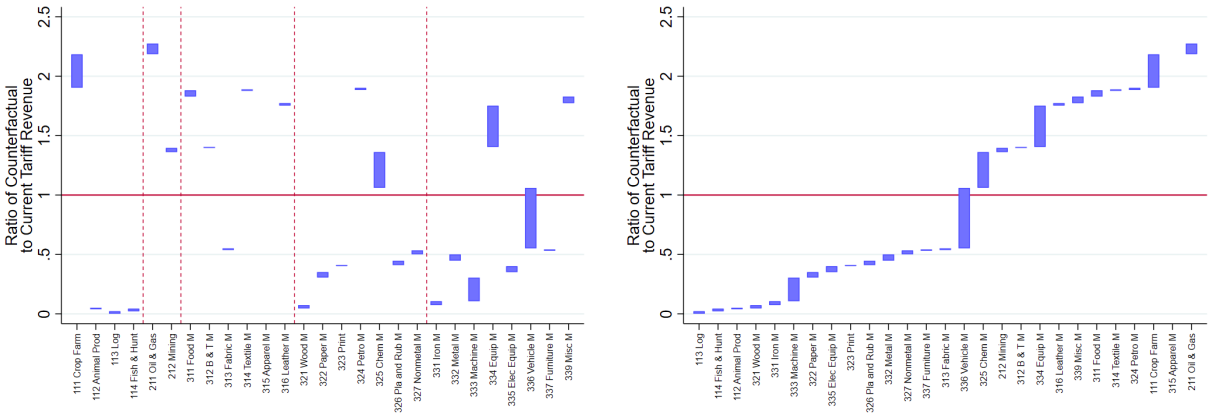
Before we move onto the next section, we discuss an implicit assumption behind our counterfactual predictions. We construct the tariff shocks using the total workforce size $\bar{L}_n$ following Blanchard et al. (2019). Though never used in the recent empirical studies such as Blanchard et al. (2019) and Lake and Nie (2021), an alternative denominator can be the number of voters, P_n. However, the summation term in equation (9) disappears if we replace $\bar{L}_n$ with P_n in the denominator. In the case of maximizing the impact of tariffs on total national votes, all g_k's are the same and policy makers do not have incentives to prioritize one sector than the other. Using P_n as the denominator corresponds to a scenario in which not-in-the-labor-force voters, such as the retired, do not care about the labor market outcomes of the workers. However, if the other voters care about labor market outcomes, either because they have family members who are working or because they perceive workers in the same county similar to themselves and consider workers' interest when formulating their political

preferences (Grossman and Helpman, 2021).

4.2 Implementing the Solution

This section implements the solution to the maximization problem (5) with particular parameterizations of the total tariff revenue T and tariff upper bound B. As mentioned in Section 2, the maximum current retaliatory tariffs on US goods are 35% and amount to 15.08% of the value of pre-trade-war US exports to China. Our baseline parameterization sets $T_0 = 0.1508 \sum_k X_k$ and $B_0 = 0.35$. We then keep $B = B_0$ and consider different values of T by scaling it with a factor of γ, i.e., $T = \gamma T_0$ for $\gamma \geq 0$. A larger γ means that the Chinese government is willing to implement a tougher retaliation. Since T does not enter the expression of g_k (see equation 6), varying it will not change the pecking order of industries. However, as we see from the algorithm to search for $\bar{k}$ at the end of the proof of Proposition 1, a higher T implies either (1) levying positive tariffs on a new industry following the pecking order or (2) increasing the tariff on the cutoff industry, $t_{\bar{k}}^r$ as in equation (8).

Figure 2: Optimal tariff scheme under different total tariff revenue constraint T, minimizing nationwide Republican voting shares



(a) Industries ranked by NAICS **(b)** Industries ranked by g_k

Notes. Both panels plot the counterfactual total tariff revenue (as multiples of current tariff revenue) above which certain industries' tariffs are activated in the solution to problem (5). Panel 2(a) ranks the industries by their NAICS three-digit codes. The dashed vertical lines in panel (a) separates two-digit NAICS industries: Agriculture (11), Mining (21), Food, Tobacco, or Textile Manufacturing (31), Material Manufacturing (32), and Machinery and Equipment Manufacturing (33). Panel 2(b) ranks industries by the value of g_k, from highest to lowest. The horizontal line indicates optimal tariffs under the current tariff revenue, and it crosses the marginal industry with a tariff $t_{\bar{k}}^r \in [0, B)$.

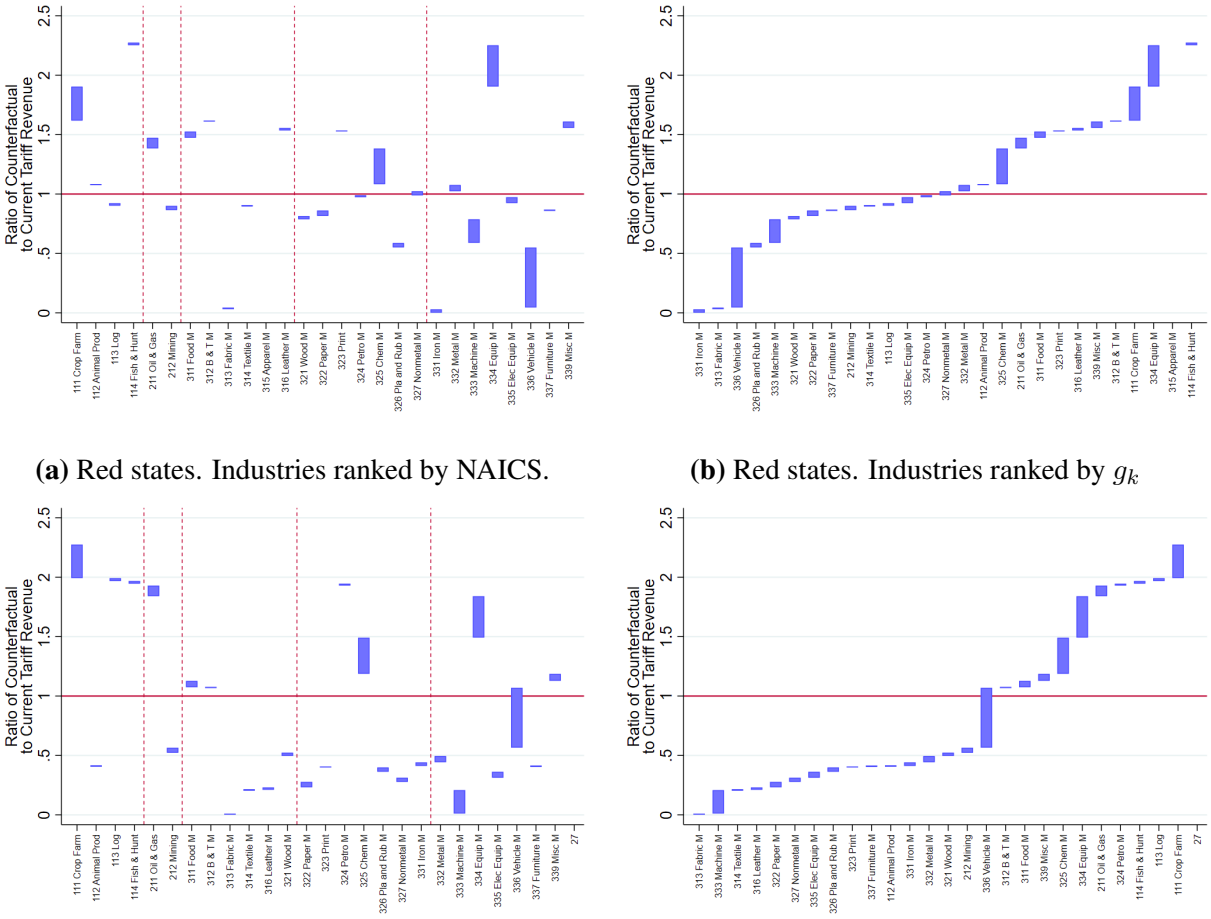
We demonstrate the solution when minimizing the nationwide Republican voting share in Figure 2. In both panels, the vertical axes indicate the ratio of the counterfactual tariff revenue to the current

tariff revenue, γ. We list NAICS two-digit industries on the horizontal axes. Panel 2(a) ranks the industries by their NAICS codes while panel 2(b) ranks the industries by the value of g_k, from the highest to the lowest. To read the figure, we first take a particular value of λ. The blue bar indicates the range of λ such that the corresponding industry is the "marginal industry" with optimal tariff $t_k^r \in [0, B_0)$. From the expression of t_k^r in equation (8), we know that the length of the bar is proportional to its pre-trade-war exports X_k. Under optimality, industries with a blue bar whose upper bound is below λ will charge the maximum tariff B_0, and industries with a blue bar whose lower bound is above λ will charge zero tariff. The blue bar of the marginal industry. As we gradually increase λ, China charges a higher tariff on the marginal industry until the tariff hits the upper bound B_0. The industry with highest g_k among the remaining industries then will become the new cutoff industry.

It is easy to read from the graph the optimal tariffs under the current tariff level, $T = T_0 = 0.1508 \sum_k X_k$. We simply draw a horizontal line at $\lambda = \frac{T}{T_0} = 1$. We find 14 industries with maximum tariff B_0 and the cutoff industry is Manufacturing of Motor Vehicles (NAICS 336). We use expression (8) and obtain the optimal tariff on this industry, 30%. A quick observation is that the optimal tariffs do not necessarily target industries with the largest exports to China. We have shown in the previous section that pre-trade-war exports are *irrelevant* in determining optimal tariffs. When minimizing the nationwide Republican voting share, industries such as Manufacturing of Chemicals (325), Manufacuring of Equipment (334) and Crop Production (111), have low g_k and should not be taxed when China wants to keep the current level of retaliation.

We can also change the set of counties from all counties in the United States to counties in certain states. In Figure 3 panels 3(a) and 3(b) illustrate the solution to minimizing the Republican voting share in all Republican winning states in the 2016 election, and panels 3(c) and 3(d) illustrate the solution to minimizing that in the swing states. One noticeable difference is that Manufacturing of Motor Vehicles (336) weighs more in Republican-winning states, and China should levy tariffs on US exports in this industry with higher priority. However, when minimizing the Republican voting share in the swing states, its priority becomes lower and serves the cutoff industry at the current tariff levels, which is similar to the case of minimizing the nationwide Republican voting share. (see Figure 2)

Figure 3: Optimal tariff scheme under different total tariff revenue constraint T, minimizing Republican voting shares in swing states or red states (2016)



(a) Red states. Industries ranked by NAICS.

(b) Red states. Industries ranked by g_k

(c) Swing states. Industries ranked by NAICS.

(d) Swing states. Industries ranked by g_k.

Notes. All panels plot the counterfactual total tariff revenue (as multiples of current tariff revenue) above which certain industries' tariffs are activated in the solution to problem (5). Panels 3(a) and 3(c) rank the industries by their NAICS three-digit codes. The dashed vertical lines in these panels separate two-digit NAICS industries: Agriculture (11), Mining (21), Food, Tobacco, or Textile Manufacturing (31), Material Manufacturing (32), and Machinery and Equipment Manufacturing (33). Panels 3(b) and 3(d) rank industries by the value of g_k, from highest to lowest. Panels 3(a) and 3(b) visualize the solution to minimizing the Republican voting shares in the Republican winning states in the 2016 election, and panels 3(c) and 3(d) visualize the solution to minimizing the Republican voting shares in the swing states. The horizontal line indicates optimal tariffs under the current tariff revenue, and it crosses the marginal industry with a tariff $t^r_{\bar{k}} \in [0, B)$.

4.3 Optimal v.s. Current Tariff

In this section, we compare the optimal retaliatory tariffs that minimize the Republican voting share in certain states with the current Chinese tariffs. We ask two closely-related questions: (1) when keeping total tariff revenue constant, how much more can optimal tariffs affect election outcomes and (2) conditional on achieving the same political outcome, how much tariff revenue can optimal tariffs save?

We have presented an algorithm to find the optimal tariff and implemented it with different tariff revenue constraints T in the previous section. To answer the first question, we set $T = T_0 = 0.1508 \sum_k X_k$ and keep the maximum tariff in each sector at $B = B_0 = 0.35$. This means that China wants to implement a tariff scheme that is of the same scale as the current one. The solution to the optimal tariffs that minimize the nationwide Republican vote share can be read off Figure 2. Industries whose corresponding blue bars are strictly below the red horizontal line should be levied the maximum tariff of 35%; those with blue bars above the red line should not be taxed; and the cutoff industry, Manufacturing of Motor Vehicles, receives a tariff between 0 and 35%. Applying the formula (8), we obtain the optimal tariff on the cutoff industry, 30%. The solution is presented in Table 2 under the column head "optimal tariff % - All states" and the associated values of g_k are also listed.

Table 2: Compare current tariff with optimal tariffs, targeting different sets of states

Industry k	X_k (billion USD)	current tariff %	$g_k \times 10^9$	optimal tariff %		
			targeting all states	All states	Swing states	Red States
111 Crop Farming	17.96	30.5	4.396	0	0	0
112 Animal Production	0.09	14.2	5.037	35	35	0
113 Logging	1.35	16.9	5.258	35	0	35
114 Fishing & Hunting	1.41	33.6	5.056	35	0	0
211 Oil & Gas Extraction	5.68	15.4	3.493	0	0	0
212 Mining	2.23	22.3	4.806	0	35	35
311 Food Manufacturing	3.37	26.2	4.674	0	0	0
312 Beverage & Tobacco	0.20	31.9	4.802	0	0	0
313 Fabric Mills	0.45	21.9	4.832	35	35	35
314 Textile Mills	0.09	19.8	4.603	0	35	35
315 Apparel Manufacturing	0.03	24.5	4.292	0	0	0
316 Leather Manufacturing	1.30	11.1	4.777	0	35	0
321 Wood Manufacturing	1.74	20.9	5.021	35	35	35
322 Paper Manufacturing	2.93	9.4	4.963	35	35	35
323 Printing	0.53	11.4	4.886	35	35	0
324 Petroleum Manufacturing	0.97	27.0	4.536	0	0	35
325 Chemical Manufacturing	19.16	11.3	4.806	0	0	0
326 Plastic & Rubber	2.30	8.6	4.882	35	35	35
327 Nonmetal Manufacturing	2.19	9.2	4.847	35	35	12
331 Iron & Steel	1.91	15.8	4.980	35	35	35
332 Metal Manufacturing	3.35	16.0	4.877	35	35	0
333 Machinery Manufacturing	12.66	10.1	4.973	35	35	35
334 Electronic Component	22.18	7.5	4.797	0	0	0
335 Electrical Equipment	3.17	19.4	4.954	35	35	35
336 Vehicle Manufacturing	32.20	15.4	4.818	31	30	35
337 Furniture Manufacturing	0.17	12.8	4.845	35	35	35
339 Misc Manufacturing	3.47	10.2	4.766	0	0	0
Targeted states vote share in 2016				48.971%	51.285%	55.695%
Vote share increased due to US tariff				0.080%	0.082%	0.088%
Vote share reduced due to current retaliatory tariff				-0.100%	-0.095%	-0.107%
Vote share reduced due to optimal retaliatory tariff				-0.105%	-0.109%	-0.130%
Total EC votes (CF2)		302		286	286	286
Total EC votes (CF3)		286		286	286	286

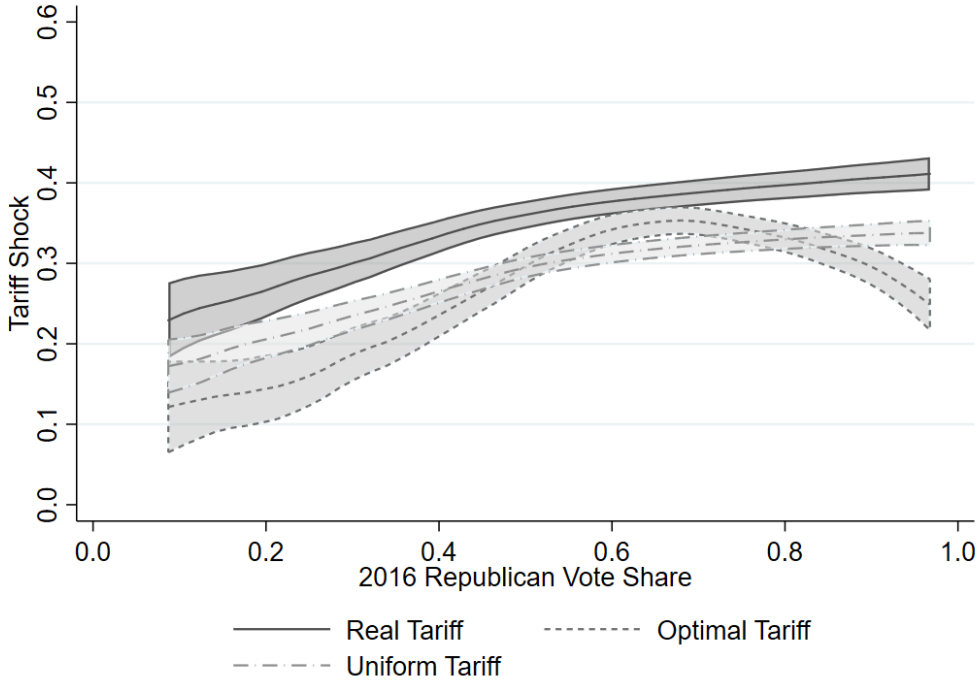
Notes. This table reports industry-level statistics of US exports, current Chinese retaliatory tariffs, value of g_k that ranks industries' priorities of getting tariffs when maximizing the political impact. g_k is computed only for minimizing total nationwide Republican votes. We report the optimal tariffs levied on each industry when minimizing total Republican votes in three sets of states: all US states in our sample, swing states in 2016 (with a winner candidate's margin smaller than 10%) and red states in 2016 (with the Republican candidate winning).

In the middle panel of Table 2, we report the voting outcomes in 2016, and the vote share change due to the current and hypothetical tariffs. For example, the nationwide Republican voting share is 48.971% in 2016 (note that Donald Trump still won the election because of the Electoral College system). According to our estimates, the actual Trump tariffs increase the share by 0.080%, and the current retaliatory tariffs reduce it by 0.100%. The optimal retaliatory tariffs will have a slightly larger impact and reduce the share by 0.105%. However, the optimal tariffs also have a larger impact in the swing state Michigan. For example, in our second counterfactual, i.e., starting from 2016 results and allowing the US tariffs and retaliatory tariffs to have an effect, the current retaliatory tariffs cannot flip the outcome in Michigan but the optimal tariffs can, reducing the total EC votes by 16. Therefore, carefully designed tariffs not only reduces the targeted outcome of nationwide Republican voting share, but also changes the total EC votes toward the Democratic candidate.

In the last two columns of Table 2, we present optimal tariffs when minimizing the Republican voting shares in the "swing states" (with a margin less than 10% in 2016) and "red states" (with the Republican winning in 2016). The optimal tariffs have a larger impact: their effects in reducing the Republican voting share are 15% and 21% larger than the current retaliatory tariffs. However, the results on the total EC votes are similar as the optimal tariffs based on all states: all of the three schemes flip the outcome in Michigan, showing a difference from the current retaliatory tariffs.

We motivate our paper by the observation that the current Chinese retaliatory tariffs fall disproportionally on counties that strongly support the Republican candidate in 2016. In Figure 4, we plot the non-parametric relationship between the retaliatory tariff shocks and the 2016 Republican voting share. Consistent with Fajgelbaum et al. (2020), we find that the current tariff shocks (labelled as "Real Tariff") are higher in counties that had stronger support for the Republican candidate in 2016. The same pattern is observed if we adopt a naive uniform tariff of 15.08% on all products. However, when the tariffs are designed to minimize the nationwide Republican voting share, counties that are closer to the middle tend to receive a larger shock. The peak appears in counties with 60% to 70% of Republican voting shares.

Figure 4: Cross-county relationship between retaliatory tariff shocks and the 2016 Republican voting share



Notes. This figure plots the county-level retaliatory tariff shocks against the 2016 Republican voting share, using a non-parametric fit as in Figure 7 of Fajgelbaum et al. (2020). We drop the counties above the 99th percentile in the distribution of tariff shocks to reduce the influence of outliers. The patterns are similar if we use different cutoff rules. (see Figure B.1)

5 Conclusion

In this paper, we take reduced-form estimates of the impact of Chinese retaliatory tariffs on the 2020 US presidential election and construct a statistical framework to study the impact of counterfactual retaliatory tariffs. We formulate an "optimal tariff" problem in which a government is seeking tariffs that generate maximum impact on the election outcomes in another country subject to linear constraints. We provide the full analytical solution to the problem and implement it using trade statistics and the reduced-form estimates. We find that the optimal tariffs can flip the outcome in certain states compared to the current tariffs.

We admit that, in this study, essential factors that can potentially change our analysis have yet to be considered. For example, we do not model how the retaliatory tariffs would hurt China, but try to capture such concerns by limiting the predicted total tariff revenue and the maximum tariff on each industry. Another important limitation is that we have ignored the general equilibrium effects of

tariffs on the labor market and political preferences in the United States. This requires a framework that connects labor market outcomes and voting behavior, which we leave for future work.

Appendix

A Additional Empirical Results

In Table A.1, we provide summary statistics of the dependent and key independent variables in regression (2).

Table A.1: Summary statistics of key county-level variables

	count	mean	sd	min	p1	p5	p10	p25	p50	p75	p90	p95	p99	max
Δ Rep vote share	3110	-0.552	2.577	-8.085	-6.076	-4.309	-3.424	-2.033	-0.634	0.774	2.110	3.072	6.354	28.161
Δ lagged Rep vote share	3110	5.885	5.212	-16.520	-6.899	-2.829	-0.382	2.652	5.507	9.478	12.753	14.782	17.456	24.290
Retaliation shock	3110	0.178	0.332	0.000	0.000	0.007	0.018	0.045	0.097	0.195	0.363	0.546	1.406	7.153
Retaliation shock (BBC)	3110	0.166	0.294	0.000	0.001	0.009	0.019	0.045	0.094	0.189	0.335	0.519	1.232	5.864
Retaliation shock (L&N)	3110	0.551	1.100	0.000	0.002	0.056	0.088	0.170	0.316	0.563	0.994	1.628	4.353	22.859
US tariff shock (L&N)	3110	1.027	1.193	0.000	0.000	0.056	0.113	0.308	0.679	1.320	2.236	3.053	5.983	12.752
US tariff shock (BBC)	3110	0.219	0.370	0.000	0.000	0.005	0.012	0.040	0.106	0.271	0.506	0.758	1.540	7.269
Agriculture subsidy	3110	0.429	1.080	0.000	0.000	0.000	0.000	0.001	0.027	0.281	1.344	2.419	4.988	15.934

In Table A.2, we categorize states in our sample by their 2016 election outcomes. The list is used when we consider minimizing the Republican voting share in different sets of states in Section 4 and 4.3.

Our main regressions in Table 1 do not allow heterogeneous treatment effects across counties or states. One may expect that the same tariff shock may induce different responses, especially depending on the county's political preferences. For example, voters that strongly support the Republicans may be more willing to endure the costs of the retaliatory tariffs. To allow for such heterogeneity, we categorize counties into three categories based on their 2016 voting outcomes: "deep blue counties" (Democratic - Republican voting share $> 10\%$), "swing counties" ($-10\% \leq$ Democratic - Republican voting share $\leq 10\%$) and "deep red counties" (Republican - Democratic voting share $> 10\%$). This categorization follows the same rules as we classify states in Table A.2. We interact binary variables that indicate whether a county belongs to the three categories with the retaliation shock T_n^r, keeping all the other variables the same as in Table 1.

Table A.3 reports the estimation results. Column (1) displays the results from Column (1) of Table 1 for ease of comparison. (we omit the other control variables for better exposition) Column (2) of Table A.3 shows the results with interaction terms, with deep blue counties as the base category. The treatment effect for the deep blue counties are twice as large as our baseline (-1.729 v.s. -0.973). The treatment effect is smaller in swing or deep red counties. This result is consistent with our

Table A.2: Categories of states by their 2016 election outcomes

Deep Blue	Swing Blue	Swing Red	Deep Red
California	Colorado	Arizona	Alabama
Connecticut	Maine	Florida	Arkansas
Delaware	Minnesota	Georgia	Idaho
Hawaii	Nevada	Iowa	Indiana
Illinois	New Hampshire	Michigan	Kansas
Maryland	New Mexico	North Carolina	Kentucky
Massachusetts	Virginia	Ohio	Louisiana
New Jersey		Pennsylvania	Mississippi
New York		Texas	Missouri
Oregon		Wisconsin	Montana
Rhode Island			Nebraska
Vermont			North Dakota
Washington			Oklahoma
			South Carolina
			South Dakota
			Tennessee
			Utah
			West Virginia
			Wyoming

Notes. "Deep blue states" refer to states with a Democratic voting share that is 10% higher than the Republican voting share in 2016. In "swing blue states", the Democratic voting share is higher but the margin is smaller than 10%. In "swing red states", the Republican voting share is higher in 2016 but the margin is smaller than 10%. Finally, "deep red states" refer to states with a Republican voting share that is 10% higher than the Democratic voting share in 2016.

earlier hypothesis that voters who strongly support the Republicans may be more willing to endure the retaliatory tariffs and the tariff shocks do not affect their voting behavior (as much as those who support Republicans less). In Appendix B.1, we check the robustness of counterfactual voting results using these estimates.

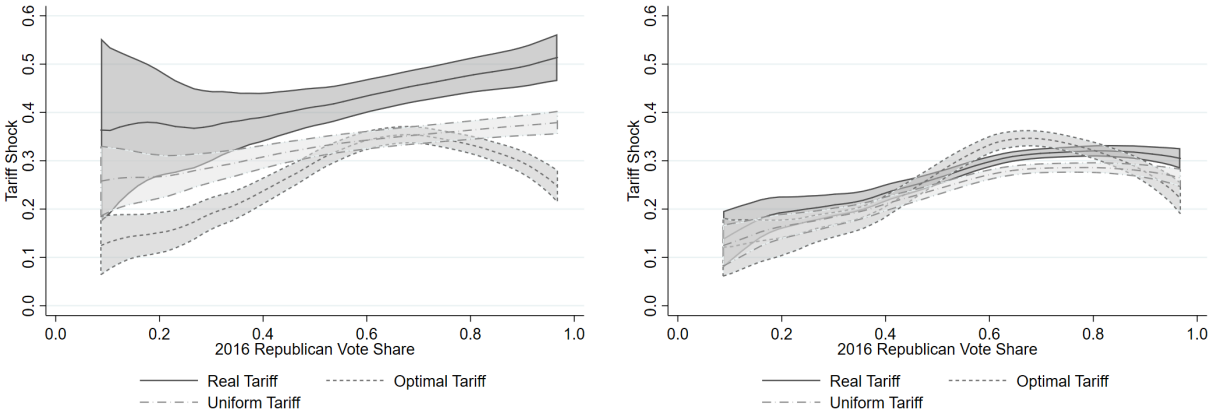
Table A.3: Heterogeneous treatment effects according to state voting outcomes in 2016

	(1)	(2)	(3)	(4)
Retaliation shock	-0.973***	-1.729**		
	(0.313)	(0.692)		
×Swing counties		0.813		
		(0.850)		
×Deep red counties		1.003		
		(0.689)		
Retaliation shock (L&N)			-0.246**	-0.413*
			(0.120)	(0.208)
×Swing counties				0.230
				(0.271)
×Deep red counties				0.227
				(0.215)
US tariff shock (BBC)	0.373**	0.370**		
	(0.163)	(0.144)		
US tariff shock (L&N)			0.183***	0.162***
			(0.050)	(0.045)
Controls & State fixed effects	Yes	Yes	Yes	Yes
R-sqr	0.852	0.864	0.852	0.864
Obs	3110	3110	3110	3110

Notes. This table reports the regressions allowing for heterogeneous treatment effects based on counties' voting outcomes in the 2016 election. We define a county to be a swing county if the absolute difference between Republican and Democratic voting shares in 2016 is below 10%. A county is defined as "deep red" if the difference between Republican and Democratic voting shares is above 10%. The base category is the "deep blue" counties. In these counties, the difference between Republican and Democratic voting shares is below -10%. The other variables are the same as in Table 1.

B Additional Quantitative Results

Figure B.1: Relationship between retaliatory tariff shocks and county-level support for the Republican candidate in 2016



(a) All counties **(b)** Drop the top 5% outliers

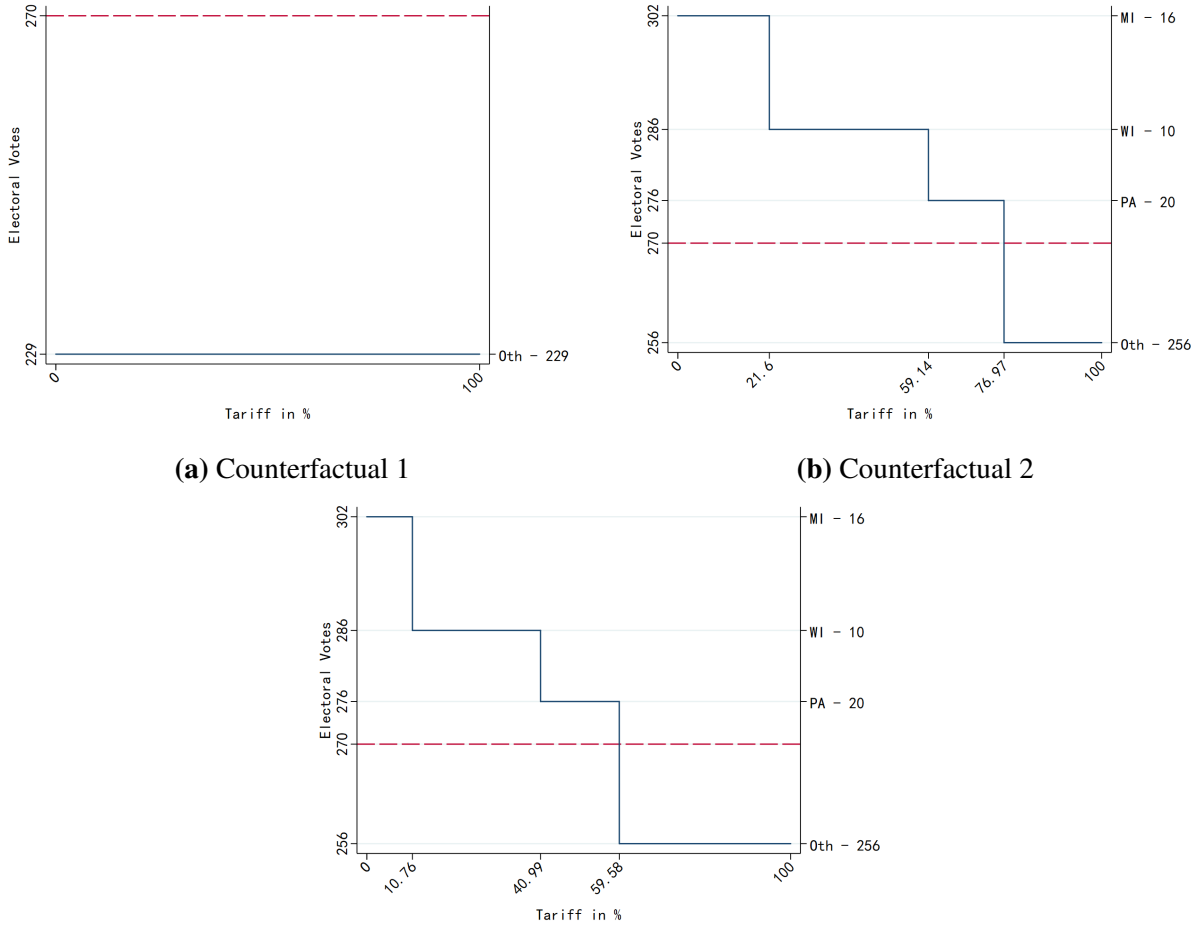
Notes. This figure plots the county-level retaliatory tariff shocks against the 2016 Republican voting share, using a non-parametric fit as in Figure 7 of Fajgelbaum et al. (2020). We include all counties in Panel B.1(a) and drop the counties above the 95th percentile in the distribution of tariff shocks in Panel B.1(b).

B.1 Allowing heterogeneous treatment effects

In figure B.2(a) of the uniform tariff with heterogeneous treatment, as we alter our China tariff strategy from 0.01% to 100%, still no change will occur to the current 2020 election result. In figure B.2(b), we observe that as we increase our uniform retaliation tariff, Michigan, Wisconsin, and Pennsylvania will be flipped, at 22%, 60%, and 77%. This results are similar to the baseline result in Section 3.

In figure B.2(c), we show that only considering China raising additional tariffs, China will flip the election result of Michigan, Wisconsin, and Pennsylvania, at 11%, 41%, and 63%.

Figure B.2: The Impact of different levels of uniform retaliatory tariffs, using estimates in Column (2) of Table A.3



(a) Counterfactual 1

(b) Counterfactual 2

(c) Counterfactual 3

Notes. We plot the predicted Electoral College (EC) votes won by Donald Trump (left y-axis) under different levels of uniform retaliatory tariffs by China (ranging from 0 to 100%). Panel (a), (b) and (c) correspond to counterfactuals 1, 2 and 3, respectively. The red dashed line denotes the minimum number of votes that Trump needs for a win (270). We illustrate the states whose results are flipped and the associated change in EC votes on the right y-axis: MI (Michigan), WI (Wisconsin) and PA (Pennsylvania).

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