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Determinants of Policy Responses in the US–China Tit-for-Tat Trade War

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We assess the economic and political factors that underpinned the scope and magnitude of tariffs and US subsidies during the US–China trade dispute. We develop a political-economy model of tariff retaliation and compensatory subsidization and econometrically quantify the determinants of trade and subsidy policies during the trade dispute. Our empirical findings confirm that political (electoral geography of targeted commodities) and economic (optimal tariff relationships, attributes of export supply and import demand, and trade balances) factors were key determinants of US policies. China's tariff retaliation was consistent with higher protectionism for larger sectors with extensive state ownership.

Key words: optimal tariffs, tariff retaliation, US–China trade war

After years of antagonistic trade rhetoric, the opening shots of the US–China trade war were fired in January 2018, setting off a trade dispute that would escalate steadily for the next year and a half and continues to persist. The initial batches of US tariffs on Chinese imports originated over multiple areas of contention: Section 201 safeguard actions toward solar panel and washing machine imports (targeting products from China as well as from other countries), a Section 232 determination related to US national security concerns over steel and aluminum imports (which also targeted imports from other countries), and US grievances based on a Section 301 investigation into unfair Chinese trade and investment practices. However, the Section 301 investigation was the primary source of contention that fueled the US–China trade war. The first round of US duties targeted major imports from China (industrial production technology, electronics, and auto parts) and was immediately met in kind by China's own retaliatory tariffs on imports from the United States, which initially focused chiefly on American agricultural products. As the dispute progressed, the list of targeted commodities expanded considerably, as did the size of the duties imposed by each country.

The first set of US Section 301 tariffs was enacted in July 2018 (the "List 1" announcement) in the form of 25% duties imposed on 818 Chinese products (defined at the 8-digit Harmonized Tariff Schedule [HTS] level), to which China's government simultaneously responded with its own 25% tariffs targeting 545 American products (defined at the 8-digit level using China's proprietary commodity nomenclature).[1] The List 1 tariffs were followed in rapid succession by tariffs on hundreds of additional commodities described in List 2 (August 2018) and List 3 (September 2018). These lists considerably expanded the scope of the tariff retaliation, with additional US duties of 25%

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[1] Information on the timeline of the dispute is taken from Bown and Kolb (2023).

and Chinese duties of between 5% and 25% on a wide array of products. While the retaliatory spiral mostly remained paused for a year until September 2019 with the introduction of the List 4a tariffs, these final rounds of tariffs were far-reaching and comprehensive, with hardly any products escaping retaliation by either side. By the time of the threatened (but never enacted) List 4b announcement, the large majority of trade in both directions was subject to duties enacted over the dispute. This study theoretically models and quantifies the factors that influenced the tit-for-tat tariff retaliation.

Only in late 2019, with the negotiation of the "Phase One" trade deal, did the retaliatory spiral halt. Among other policy commitments, the Phase One deal committed the Chinese government to undertake $80 billion in expanded purchases of American agricultural products over 2020–2021, though its actual purchases fell far short of this target (Bown, 2022; Muhammad, Smith, and Grant, 2022). However, the majority of the Section 301 tariffs imposed between July 2018 and September 2019 remain in place to date. The new purchase agreement coincided with the resumption of much of the trade that had existed prior to the dispute, but bilateral trade volumes have generally remained below their predispute levels, in spite of China's purchase targets.

The back-and-forth retaliation between the two trading powers offers a classic illustration of strategic tariff-setting and political motives in trade policy. The US tariffs targeted prominent Chinese products in strategically important industries; similarly, China's tariffs targeted major products in export-oriented US industries (e.g., agriculture and auto production). China's list of targeted products significantly impacted industries in electorally sensitive US regions (e.g., agriculture-reliant Midwestern states), which created political ramifications in addition to the tariffs' economic impacts (Blanchard, Bown, and Chor, 2019; Fetzer and Schwarz, 2021; Kim and Margalit, 2021). The US government responded to these trade actions with ad hoc support to farmers in the form of Market Facilitation Program (MFP) payments, which over the course of the dispute provided roughly $28 billion in production-coupled subsidies for producers of soybeans, corn, wheat, cotton, and many other commodities (Glauber, 2021). Concerns over possible political motivations underlying the program's design were raised often. Indeed, Senate Democrats in early 2020 questioned then-US Secretary of Agriculture Sonny Perdue over whether the MFP payments were biased toward particular regions, and some researchers have offered quantitative evidence that this was indeed the case (Choi and Lim, 2023). The MFP payments remained available to farmers through early 2020 based on eligible production from the 2019 marketing year, until the program was discontinued following the signing of the Phase One deal. We theoretically model and empirically quantify the determinants of MFP payments.

The literature assessing the economic and political determinants of trade protectionism and retaliation is well-established.[2] The factors that determine which industries and interest groups benefit from favorable trade policy have been extensively explored, for example, in the well-known works of Grossman and Helpman (1994, 1995). These theoretical formulations of political economy considerations have been accompanied by a supporting body of empirical work (Kroszner and Irwin, 1996; Goldberg and Maggi, 1999; Gawande and Bandyopadhyay, 2000; Mitra, Thomakos, and Ulubaşoğlu, 2002; Dutt and Mitra, 2005), including studies that focus on the political economic aspects of government support and protectionism in food and agriculture (Lopez and Matschke, 2006; Klomp and de Haan, 2013). Similarly, analyses of optimal strategic tariff-setting are extensive, reflecting both theoretical (Kennan and Riezman, 1988; Felbermayr, Jung, and Larch, 2013) and empirical (Broda, Limão, and Weinstein, 2008; Ossa, 2014; Nicita, Olarreaga, and Silva, 2018) approaches.

Our study is also situated in the broader literature on tit-for-tat tactics in international trade policy encompassing the use of both tariff and nontariff policy instruments. In this area, related work includes Blonigen and Bown (2003), who show that the threat of retaliatory antidumping actions by

[2] Political economy approaches have also been widely employed to analyze adjacent issues such as foreign investment policy (Branstetter and Feenstra, 2002) and free trade agreements (Maggi and Rodríguez-Clare, 2007). More broadly, such analyses have also been used to investigate features of market structure and policy considerations on topics such as environmental protection (List and Sturm, 2006) and migration (Razin, Sadka, and Swagel, 2002), among others.

foreign trading partners typically diminishes the frequency and scope of US antidumping petitions. Similarly, Feinberg and Reynolds (2006) demonstrate that tit-for-tat retaliation is a key factor in explaining the prevalence of antidumping actions in global trade. Finally, and of particular relevance for agricultural trade policy, Nes and Schaefer (2022) document that the application of sanitary and phytosanitary (SPS) standards by importing countries tends to spur retaliatory tit-for-tat responses by affected exporting countries.

The US–China trade war has also given rise to a large and growing literature analyzing the origins and impacts of the dispute (see, among others, Liu and Woo, 2018, or Bown, 2019). These studies largely focus on quantifying the direct and indirect effects of the trade restrictions and other policy actions undertaken by both countries on trade and investment volumes (Amiti, Kong, and Weinstein, 2020; Mao and Görg, 2020), as well as production, consumption, prices, and the welfare of impacted groups and industries (Amiti, Redding, and Weinstein, 2019; Itakura, 2020; Li, Balistreri, and Zhang, 2020). Closely related to our own analysis is the recent work of Choi and Lim (2023), who assess the degree to which US and Chinese trade policies toward the agricultural sector enacted during the dispute influenced the outcome of the 2020 US presidential election.

The impacts of the dispute on US agriculture have also spurred the development of a sizable body of literature, one that largely consists of *ex post* analyses of the dispute's impacts. Early work assessed the effects of the dispute in its early stages; for example, Marchant and Wang (2018) describes the potential impacts of the dispute on agriculture during the trade war's nascency. The bulk of the follow-on work considers the effects of the retaliatory tariffs on US and world agriculture at large or on individual sectors. Studies by Carter and Steinbach (2020) and Grant et al. (2021) analyze the impacts of China's tariff retaliation on US agricultural products. Several other works analyze the impacts of the trade conflict on particular commodities and sectors, including soybeans (Sabala and Devadoss, 2019; Adjemian, Smith, and He, 2021), sorghum (Zhang and Marchant, 2019; Sabala and Devadoss, 2022), cotton (Sabala and Devadoss, 2021), corn (Balistreri et al., 2018), and poultry (Unveren and Luckstead, 2020). The effects of the MFP subsidy program have also come under focus. Janzen and Hendricks (2020) analyze whether the MFP payments were sufficient to compensate US farmers for export losses from the dispute, finding that the subsidy payments more than offset the negative impacts of the trade disruptions on the US farm sector. Considering the broader implications of the MFP payments, Glauber (2021) assesses whether the program ran afoul of US World Trade Organization (WTO) commitments on allowable support rates, describing the possibility that the program could serve as the basis for formal complaints by other countries to the WTO over US trade practices. Finally, Yu, Villoria, and Hendricks (2022) investigate the impacts of China's retaliatory tariffs on farmland rental rates at the US county level.

Despite the existence of a comprehensive literature on the broader economic and political aspects of strategic protectionism and the burgeoning body of research assessing the *ex post* impacts of the tariffs and subsidies enacted during the US–China dispute both within and beyond the agricultural sector, limited efforts have been made to systematically quantify the *ex ante* factors that underpinned the tariff and subsidy actions undertaken during the dispute. The US–China trade war offers an ideal setting with which to explore these considerations in a comprehensive framework given that the dispute endured for nearly 4 years, covered billions of dollars in trade, and impacted a wide range of products. Given the economic significance and the intensity of the dispute, this paper aims to (i) theoretically model the factors that influenced the tariff retaliation, (ii) econometrically quantify the effects of the determinants on the scope and magnitude of the vigorous tit-for-tat tariff retaliations, and (iii) analyze the factors that influenced US policymakers in subsidizing impacted industries.

To accomplish these objectives, we first develop a theoretical framework that captures political economy considerations (i.e., lobbying efforts, electoral factors, and the special interests of industry groups) and economic determinants (sectoral features and optimal tariff considerations) along the lines of Grossman and Helpman (1994) (henceforth, GH). Critically, we extend the GH framework to account for several salient features of the US–China dispute. First, we account for differences in the political incentives facing the democratic US government and the nondemocratic Chinese government. While many frameworks besides that of GH exist with which to consider the political economy origins of trade policy, this particular setting allows us to systematically investigate how the weight of various interest groups in policymakers' objective functions, in addition to traditional economic determinants of trade policy, led to the specific policy outcomes of the dispute. Second, we advance GH's model by incorporating domestic subsidies, a key element of the US policy response.

To empirically implement the theoretical model, we construct a detailed database covering the products impacted by tariff retaliation, the level of tariffs imposed, and the specific timing of the tariff actions using the original documents from the US Trade Representative (USTR) and the Chinese Ministry of Commerce (MOC). We also develop a novel dataset describing commodity-level MFP subsidy payment rates. Based on this, we econometrically quantify the role of the salient economic and political factors that determined the size and scope of the policy actions by both sides of the dispute.

Theoretical Model

The dispute between the United States and China was characterized by counterpunches of tariff retaliations on various commodities and the implementation of ad hoc US subsidy programs to mitigate trade damages caused by China's tariffs. As described above, the policy actions of the two countries reflected both economic and political considerations. To formally model the determinants of these policy actions, we develop a theoretical framework that characterizes the strategic and noncooperative undertaking of trade and subsidy policies between two countries. We base our analysis on the seminal work of Grossman and Helpman (1995) (GH), but we modify and extend their theoretical framework to explicitly account for the relevant economic and political features that characterized the dispute between the United States and China.

The GH framework considers two large countries comprised of consumers and producers in multiple sectors. In a noncooperative trade war, governments set reactionary trade policies toward each industry to maximize their respective national welfare functions: a weighted sum of consumer surplus, domestic industry profits, endogenous lobbying contributions from industry groups, and tariff revenues. We modify and extend the GH framework in two key ways in order to capture the specific features of the US–China dispute and to generate testable empirical predictions regarding the factors that underpinned the tariff and subsidy actions undertaken during the dispute.

First, we account for the notion that the Chinese government, as a one-party nondemocratic state, faces a starkly different set of political incentives than do US policymakers. To this end, we replace the symmetric governments of the GH framework with a democratic government (the United States) that responds to "politically important" industry groups that make endogenous political contributions and a nondemocratic one (China) that does not. However, we accommodate the possibility that different industries enter into the nondemocratic government's decision making with varying importance, and an element that we incorporate to capture the notion that nondemocratic governments might still emphasize the welfare of certain groups (e.g., sectors with extensive government ownership or those located in certain regions) over others.[3]

Second, we introduce domestic production subsidies into the GH framework to capture the role of the US MFP payments enacted during the dispute. The US government thus considers two policy dimensions—import tariffs and domestic production subsidies—when determining its optimal actions toward each sector. By introducing this feature, our model more comprehensively accounts for the set of policy actions undertaken during the dispute than does the canonical GH model or similar frameworks.

[3] Several studies have considered the differences in incentives faced by democratic versus nondemocratic policymakers. For example, Henisz and Mansfield (2006) theoretically analyzed the differences in the determination of optimal trade policy between these two government types. Mitra, Thomakos, and Ulubaşoğlu (2002) empirically compare the weight assigned by policymakers to national welfare versus lobbying contributions in democratic versus nondemocratic eras in Turkey.

Model Setup and Noncooperative Policy Equilibrium

Based on the above description of the US–China trade war, we develop a two-country model covering producers and consumers of multiple goods, political economy of lobbying efforts and the nondemocratic government's interest in state-owned industries, and retaliatory tariffs by both countries and subsidy provision. Using this model, we derive equilibrium relationships describing the *ex ante* determinants of political and economic factors that influenced the scope and magnitude of tariff and subsidy policies.

Though our framework is readily applicable to the US–China trade war, we maintain the generality of the model by denoting the home country as the democratic country and the foreign country as the nondemocratic country (with variables for the foreign country denoted by *). Each country is comprised of utility-maximizing consumers that consume a numeraire, z, and nonnumeraire, c_i, goods, with $i = 1, \ldots, n$. In the home country, owners of the specific factor in industry i engage in costly electoral efforts (voting, political contributions), denoted by C_i, for the purpose of receiving favorable policy treatment (i.e., protectionist tariffs and/or production supports).

The two governments noncooperatively set trade policies (import tariffs) and domestic policies (production subsidies) for each nonnumeraire good. The home country's import tariff is described by $\boldsymbol{\tau} = (\tau_1, \tau_2, \ldots, \tau_n)$ describes, with gross *ad valorem* tariff rate $\tau_i = (1 + t_i)$ and net tariff rate $t_i > 0$. The per unit production subsidy schedule of the home country is denoted by $\boldsymbol{\sigma} = (\sigma_1, \sigma_2, \ldots, \sigma_n)$, with $\sigma_i = (1 + s_i)$ and $s_i > 0$ denoting the net subsidy rate, which we model as *ad valorem* price supports.[4] Contingent on the optimal electoral contribution schedule of domestic industries, the home country government considers the total electoral contributions received from individual industries along with the overall welfare of individuals in setting its policies to maximize the objective function

$$G = \sum_{i \in L} C_i(\boldsymbol{\tau}, \boldsymbol{\sigma}, \boldsymbol{\pi}) + aW(\boldsymbol{\tau}, \boldsymbol{\sigma}, \boldsymbol{\pi}), \text{ with } a \geq 0, \tag{1}$$

where L indicates the set of industries that make electoral contributions to the policymakers, and a is the weight that the government assigns to national welfare relative to the contributions it receives. National welfare is given by

$$W(\boldsymbol{\tau}, \boldsymbol{\sigma}, \boldsymbol{\pi}) = l + \sum_{i=1}^{n} \Pi_i(\tau_i, \sigma_i, \pi_i) + \mathrm{CS}(\boldsymbol{\tau}, \boldsymbol{\sigma}, \boldsymbol{\pi}) + \mathrm{TR}(\boldsymbol{\tau}, \boldsymbol{\sigma}, \boldsymbol{\pi}) - \mathrm{SC}(\boldsymbol{\tau}, \boldsymbol{\sigma}, \boldsymbol{\pi}), \tag{2}$$

where $l = \sum_{i=1}^{n} l_i$ indicates total payments to labor (with wages normalized to 1), $\Pi_i(\cdot)$ represents firm profits, $\mathrm{CS}(\cdot)$ is consumer surplus, $\mathrm{TR}(\cdot)$ is total tariff revenues, and $\mathrm{SC}(\cdot)$ are subsidy costs.

Conversely, by virtue of its nondemocratic nature and the resulting assumption that no endogenous lobbying activities take place, the foreign government's welfare function is assumed to only consist of the explicit economic components of national welfare:

$$\begin{aligned} G^* = W^*(\boldsymbol{\tau}^*, \boldsymbol{\sigma}^*, \boldsymbol{\pi}) = l^* + \sum_{i=1}^{n} b_i^* \Pi_i\left(\tau_i^*, \sigma_i^*, \pi_i\right) \\ + \mathrm{CS}(\boldsymbol{\tau}^*, \boldsymbol{\sigma}^*, \boldsymbol{\pi}) + \mathrm{TR}(\boldsymbol{\tau}^*, \boldsymbol{\sigma}^*, \boldsymbol{\pi}) - \mathrm{SC}(\boldsymbol{\tau}^*, \boldsymbol{\sigma}^*, \boldsymbol{\pi}). \end{aligned} \tag{3}$$

To account for the notion that particular industries in the foreign country might possess greater political clout (and the welfare of which would thus weigh more heavily in the foreign government's objective function) even in the the absence of electoral considerations, we introduce the parameter

[4] We specify subsidies as production-coupled payments because the MFP payments (which we discuss in more detail when describing our data) were tied to actual production (Coppess et al., 2019).

$b_i^* \geq 1$. This parameter assigns varying weight to the profits of individual industries similar in function to the political economy variable, $C_i(\cdot)$, in the home country's objective function. We introduce this political economy measure in this fashion to appropriately capture the Chinese political context. For instance, b_i^* captures the prominent role in policy making played by state-owned enterprises (SOEs) in certain sectors, which maintain political influence by virtue of their direct ties to the government (Bai et al., 2020; Bombardini, Cutinelli-Rendina, and Trebbi, 2021).

Governments in both countries maximize their respective objective functions, with the home country government taking the electoral contributions of each industry group as given, to set trade and domestic policies noncooperatively. We define $M_i(\tau_i,\sigma_i,\pi_i) \equiv D_i(\tau_i\pi_i) - X_i(\sigma_i\tau_i\pi_i)$ as the home country's net imports of good i (domestic demand D_i minus domestic supply X_i), I_{iL} as a dichotomous variable indicating whether a home-country industry makes electoral contributions, ε_i^* as the elasticity of foreign export supply, and α_L as the share of the population in politically active sectors. Simplification of the first-order conditions and enforcing world market clearing leads to optimal tariff and domestic subsidy responses. We first consider the home country's optimal tariff response, τ_i^o, given by

$$\text{(4)} \qquad \left(\tau_i^o - 1\right) = \underbrace{\frac{M_i'}{M_i' - (\sigma_i - 1)\sigma_i X_i'}}_{\text{(i)}} \left[-\underbrace{\frac{(I_{iL} - \alpha_L)\sigma_i X_i}{(a + \alpha_L)\pi_i M_i'}}_{\text{(ii)}} + \underbrace{\frac{1}{\varepsilon_i^*}}_{\text{(iii)}} + 1 \right] - 1.$$

Term (i), which is less than or equal to 1, is a function of the sensitivity of the home country's import demand and domestic supply functions to changes in price (M_i' and X_i'), and production subsidies (σ_i). Because $\sigma_i \geq 1$, and owing to the slope of the import demand and domestic supply functions with respect to price ($M_i' < 0$ and $X_i' > 0$), term (i) is necessarily positive. Term (i) thus describes that tariff rates are higher in industries for which domestic supply is relatively inelastic to changes in prices (low X_i').

Term (ii) in equation (4) mirrors the analogous political economy term in GH, in that it reflects how the deadweight losses associated with tariffs are balanced against the political support from industry groups in shaping the government's policy actions. Industries that "matter" in political and electoral terms in the politicians' objective function (i.e., industries for which $I_{iL} = 1$) are the beneficiaries of higher tariffs on competing imports relative to industries that do not make political contributions to policymakers. The optimal tariff incentives as reflected in term (ii) are also increasing in the magnitude of the subsidy rate (σ_i) and the size of the domestic industry (X_i).

Term (iii) in equation (4) captures the familiar market power (i.e., terms of trade) considerations in tariff-setting by a large country, as the home country's optimal tariff is proportional to the inverse of the elasticity of the foreign country's export supply (ε_i^*). Intuitively, the more inelastic is the foreign country's export supply for good i (lower ε_i^*), the higher is the optimal tariff that the home country will impose to exploit its market power in the world market.

Next we analyze the home country's optimal subsidy, which is given by

$$\text{(5)} \qquad \left(\sigma_i^o - 1\right) = \underbrace{\frac{(I_{iL} - \alpha_L)X_i}{(a + \alpha_L)\pi_i\tau_i X_i'}}_{\text{(iv)}} - \underbrace{\frac{M_i}{\tau_i\pi_i\left(\tau_i D_i' + \tau_i^* M_i^{*\prime}\right)}}_{\text{(v)}} - \underbrace{\frac{(\tau_i - 1)\tau_i^* M_i^{*\prime}}{\tau_i\left(\tau_i D_i' + \tau_i^* M_i^{*\prime}\right)}}_{\text{(vi)}}.$$

The magnitude of production subsidies in equation (5) is determined by three components: political considerations, the terms-of-trade effects, and tariff revenue effects. Though the political economy term embodies similar elements to the corresponding term in equation (4), several key differences exist between the two equations. Term (iv) shows that industries with large volumes of production (e.g., soybeans) have extensive connections to politicians and the monetary resources to navigate the inner workings of the political process and thus lobby intensively to secure higher subsidies. This prediction of the model accords with how US subsidy policies were formulated during the trade dispute, as the large, politically salient US farm sector—which spans many of the most electorally important regions of the United States and whose stakeholders engage in extensive lobbying efforts—was far and away the biggest winner with regard to the government's subsidization efforts.

The sign of term (v)—and thus whether the term plays a positive or negative role in shaping the incentives of policymakers to furnish subsidies—depends on whether the commodity is imported or exported by the home country. For importing sectors (sectors for which $M_i > 0$), term (v) is positive, indicating there is an incentive to enact higher subsidies if the volume of imports is larger. Subsidies provided by an importing country induce higher domestic production, which depresses the import price and thus improves the terms of trade. If the home country is an exporter of this commodity ($M_i < 0$), policymakers are incentivized to offer lower subsidy rates because higher domestic production subsidies will lower the export price and deteriorate the terms of trade. Ultimately, the magnitude of the effect of term (v) depends on the price sensitivity of domestic demand (D_i') and foreign import demand ($M_i^{*'}$), as the terms-of-trade impacts are mediated by the degree to which domestic consumption and foreign trade adjust in response to the home country's production subsidy.

Because we do not consider export subsidies or taxes (i.e., $\tau_i = 1$ for exports), term (vi) disappears for exporting industries. If the good is an import good, then σ_i is a production subsidy and the home country maintains an import tariff (i.e., $\tau_i \geq 1$). In this case, term (vi) is negative and captures the relationship between the magnitude of the tariff and the production subsidy maintained by the government.

Next, we present the foreign country's optimal policy actions, which are given by

$$(4^*) \qquad \left(\tau_i^{o*} - 1\right) = \underbrace{\frac{M_i^{*'}}{M_i^{*'} - \left(\sigma_i^* - 1\right)\sigma_i^* X_i^{*'}}}_{(\mathrm{i}^*)} \left[\underbrace{\frac{-\left(b_i^* - 1\right)\sigma_i^{o*} X_i^*}{\pi_i M_i^{*'}}}_{(\mathrm{ii}^*)} + \underbrace{\frac{1}{\varepsilon_i}}_{(\mathrm{iii}^*)} + 1 \right] - 1,$$

$$(5^*) \qquad \left(\sigma_i^{o*} - 1\right) = \underbrace{\frac{\left(b_i^* - 1\right) X_i^*}{\pi_i \tau_i^{o*} X_i^{*'}}}_{(\mathrm{iv}^*)} - \underbrace{\frac{M_i^*}{\tau_i^* \pi_i \left(\tau_i^* D_i^{*'} + \tau_i M_i'\right)}}_{(\mathrm{v}^*)} - \underbrace{\frac{\left(\tau_i^* - 1\right)\tau_i M_i'}{\tau_i^* \left(\tau_i^* D_i^{*'} + \tau_i M_i'\right)}}_{(\mathrm{vi}^*)}.$$

These expressions are similar to their counterparts describing the home country's policies, except for the modified political economy elements in terms (ii*) and (iv*). Therefore, the interpretations of these two equations (but for the political terms) exactly follow those in equations (4) and (5). Because of the negative sign of $M_i^{*'}$ and the assumption of $b_i^* \geq 1$, term (ii*) describes that industries whose profits receive higher weight in the government's objective function (higher b_i^*), as well as larger industries (higher X_i^*), benefit from higher levels of protectionism. Similarly, term (iv*) indicates that larger, more politically connected industries tend to benefit from higher subsidies. This mirrors the reality of the Chinese political context, in which the government provides extensive support for particular industries and firms (Lee, Walker, and Zeng, 2014).[5]

To conclude, the theoretical model and analytical results highlight the influence of political lobbying, volume of production, terms of trade, and the responsiveness of export supply and import demand on both countries' tariff and subsidy actions. Having established the theoretical relationships and hypotheses relating policy decisions to fundamental economic and political factors, we next turn to estimating these relationships in an econometric setting.

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[5] While many of China's large export industries were targeted by significant US tariffs, China's government did not systematically provide subsidies in response to the US–China trade war. Therefore, even though we consider the incentives for producer subsidization by a nondemocratic country in the theoretical analysis, we do not empirically analyze China's subsidy actions (or lack thereof) as part of the broader US–China dispute.

Empirical Approach and Data

Based on the optimal policy actions described in theoretical equations (4), (4*), and (5), in this section we develop the econometric approach to analyze the factors that shaped the policy actions taken by both countries in the US–China trade dispute. To do this, we estimate reduced-form empirical relationships corresponding to the US tariffs on Chinese imports (equation 4), the Chinese retaliatory tariffs on US imports (equation 4*), and the compensatory US production subsidies (equation 5), each as a function of political and economic variables as predicted by the theoretical analysis. As indicated earlier, we confine our focus in the tariff analysis to the multiple rounds of tariffs implemented under the Section 301 dispute.[6] It is important to note that the scope of US Section 301 tariffs largely pertained to which products were covered rather than the level of tariffs, with the large majority of the imposed tariffs being 25% *ad valorem*. Consequently, we implement the empirical model of US tariffs based on a binary classification of whether a particular product was targeted under the various US tariff actions.[7] Because trade and subsidy policies were enacted at the product level, we conduct the analysis across individual 6-digit Harmonized System (HS) commodities.[8]

We denote the values of US variables with superscript *u* and China's variables with superscript *c*. The econometric specifications describe the factors that determined a particular policy action toward a particular commodity in relation to empirical analogues to the factors depicted in the theoretical results. These relationships are captured separately by (i) an indicator variable reflecting whether the United States imposed tariffs on Chinese exports of a particular commodity under the various Section 301 actions ($I\left(t_i^u > 0\right)$), (ii) the level of the *ad valorem* rates for the Chinese retaliatory tariffs on US exports (t_i^c), and (iii) the *ad valorem* equivalent of the MFP subsidy payments offered by the US government (s_i^u).

$$
\begin{aligned}
I\left(t_i^u > 0\right) = {} & \alpha_1 \mathit{Red\text{-}state\ share}_i + \alpha_2 X_i^u + \alpha_3 \mathit{Imp.\ share}_i^{u,c} + \alpha_4 \left(1/\varepsilon_i^c\right) \\
& + \alpha_5 t_{i,MFN}^u + \sum_{k=1}^{7} \alpha_6^k BEC_i^k + \eta_i^u,
\end{aligned}
\tag{6}
$$

$$
\begin{aligned}
t_i^c = {} & \beta_1 \mathit{SOE\ share}_i + \beta_2 X_i^c + \beta_3 \mathit{Imp.\ share}_i^{c,u} + \beta_4 \left(1/\varepsilon_i^u\right) \\
& + \beta_5 t_{i,MFN}^c + \sum_{k=1}^{7} \beta_6^k BEC_i^k + \eta_i^c,
\end{aligned}
\tag{7}
$$

$$
\begin{aligned}
s_i^u = {} & \gamma_1 t_i^u + \gamma_2 t_i^c + \gamma_3 \mathit{Red\text{-}state\ share}_i + \gamma_4 X_i^u + \gamma_5 M_i + \gamma_6 \mathit{Imp.\ share}_i^{c,u} \\
& + \sum_{k=1,2} \gamma_7^k BEC_i^k + \nu_i^u.
\end{aligned}
\tag{8}
$$

[6] We specifically analyze the Section 301 tariffs because the Section 301 dispute was specific to the United States and China and was the most far-reaching of the various US trade conflicts begun during this period. To illustrate, the Section 301 trade actions targeted around $517 billion worth of Chinese exports to the United States, compared to the other trade actions, which affected only around $13.1 billion worth of exports from all targeted countries in total, just a small portion of which were Chinese exports (Bown, Jung, and Lu, 2018a, from).

[7] In contrast, China's tariff rates differed considerably both within and across its retaliatory actions, taking values of 5%, 10%, 15%, 20%, or 25% across products.

[8] In the estimation, we also include those commodities that were not targeted by retaliatory tariffs or subsidies during the various stages of the dispute, which avoids sample selection issues of focusing only on targeted commodities. However, for our empirical analysis of subsidy payments under MFP, we focus only on food and agricultural commodities, as these commodities were the only products to receive compensatory subsidies from the US government.

Political economy factors are incorporated via two distinct measures in the US and Chinese tariff specifications. For the US tariff specification, the variable *Red-state share*, with associated coefficient α_1, measures the share of total US production in each commodity i's parent industry for 2017 that occurred in states that voted Republican in the 2016 presidential election. The rationale for the use of this measure is that, as implied in the theoretical framework, the economic fortunes of industries predominantly located in politically important states are more likely to influence the actions of US policymakers trying to curry electoral favor. To capture political considerations in China as relating to government ownership we introduce $SOE\ share_i$ with associated coefficient β_1, which, for each commodity i, measures the share of SOEs in total revenues in each commodity's Chinese parent industry in 2017.[9] We anticipate that estimates on both coefficients should be positive reflecting the role of political considerations in determining tariff responses.

The other components of equations (6) and (7) relate to the economic factors described in the theoretical result in equation (4). The industry size terms (X_i^u and X_i^c with associated coefficients α_2 and β_2) reflect the theoretical result that larger industries are likelier to benefit from higher levels of protectionism. Because data on product-level production across the more than 5,000 6-digit HS commodities are not available, we capture total industry supply by using total US or Chinese exports in commodity i's 4-digit HS category to the rest of the world (in billions USD for 2017).[10, 11]

To proxy for the sensitivity of each country's import demand functions (M_i' and $M_i^{*'}$ in the theoretical model), we compute country-specific import shares for each commodity based on trade statistics from CEPII's BACI dataset (Gaulier and Zignago, 2010). $Imp.\ share_i^{u,c}$ is defined as the ratio of US imports of commodity i from China relative to total US imports of that commodity. Similarly, $Imp.\ share_i^{c,u}$ is the ratio of China's imports of commodity i from the United States to total Chinese imports of that commodity. These variables implicitly captures the features of each country's import demand curve based on the idea that if a country's import share for a given commodity sourced from a particular country is low, then the import demand curve is likely to be relatively more sensitive to changes in the price of the imported good from that particular partner (Devadoss, Luckstead, and Ridley, 2019). To capture terms of trade effects mediated by the sensitivity of exports to price changes, we include estimated values of the (inverse) elasticity of export supply ($1/\varepsilon_i$) for both US and Chinese exports at the 4-digit HS level based on bilateral trade data for China and the United States (using annual data for the years 2012–2019) obtained using Soderberry's (2015) limited information maximum likelihood estimation approach.[12]

To control for pre-trade-war tariff rates and the possibility that the duties imposed during the dispute may have depended on existing tariff levels, we incorporate the respective countries' MFN

[9] To compute *Red-state share*, we first assign each commodity to one of 22 unique 3-digit NAICS sectors using Pierce and Schott's (2012) commodity-industry crosswalk and then calculate the ratio of the red-state value of production to the US total value of the industry's gross output (from Bureau of Economic Analysis data). Similarly, we compute *SOE share* by mapping each commodity to a 2-digit ISIC industry, and compute SOEs' shares of industry revenues based on data from the Chinese National Bureau of Statistics' *China Statistical Yearbook* for 2018. Additional details on the construction of these two measures is provided in the online supplement (see www.jareonline.org).

[10] We note that total production and total exports are typically closely linked with one another across commodities, suggesting that the former measure largely captures the same information as the latter measure. To verify this, we have obtained data on 2017 US agricultural production and exports from the FAS Production, Supply, and Distribution database, which records information on 56 primary and processed agricultural products. The correlation between exports and production in this dataset is calculated to be 0.89, implying that production and exports tend to maintain very close relationships with one another.

[11] Because our theoretical modeling framework considers industries rather than commodities, we compute total exports at the HS 4-digit level rather than the 6-digit level because the 4-digit level tends to better reflect the definition of an industry. To illustrate with an example, the 4-digit HS heading 0805 (citrus fruit) includes the 6-digit HS subheadings 080521 (mandarins), 080522 (clementines), 080529 (other oranges), and 080540 (grapefruit and pomelos). It is reasonable to assert that the 4-digit designation offers a more meaningful description of an industry in this instance, given the narrow distinctions between the different goods in this category. We present results based on proxying total production by using total exports at the 6-digit HS level in the online supplement. Our results are qualitatively similar under this alternative specification.

[12] We estimate these values at the 4-digit level because data and computational limitations make it impractical to estimate these values at the 6-digit level. The online supplement describes the approach to estimating export supply elasticities and provides detailed summary statistics on the estimated elasticities.

tariff rates ($t^u_{i,MFN}$ and $t^c_{i,MFN}$) obtained from the World Bank's World Integrated Trade Solution (WITS) database. To account for broad industry features, we include in each equation a set of indicator variables, BEC^k_i, where $k = 1, \ldots, 7$, that records the Broad Economic Categories (BEC) classification of each commodity i; these are equal to 1 if commodity i belongs to either of the seven top-level BEC classifications, and 0 otherwise.[13] Finally, η^u_i and η^c_i are mean-zero error terms in the US and Chinese tariff specifications, respectively.

The level of US MFP subsidy payments by commodity is analyzed in equation (8), which encompasses similar elements as the tariff equations but with several differences that reflect the optimal subsidy relation described in the theoretical model. Similar to the US tariff equation, political factors are incorporated via the *Red-state share*$_i$ term with associated coefficient γ_3. This variable reflects the same political incentives embodied in the analogous term in the US tariff expression and in the subsidy expression in theoretical equation (5), indicating that subsidies will typically be higher in electorally important industries.

We also expect that producers of commodities with higher total volumes of production (X^u_i) were the recipients of higher payment rates, in line with the high MFP payment rates received by producers of many major US agricultural commodities. US exports from the United States to China are captured by the variable M_i, defined as net US–China exports at the 6-digit commodity-level calculated based on BACI trade data. Commodities for which China imports significant volumes from the United States (high M_i) are likely to receive high levels of support.

The import share variable *Imp. share*$^{c,u}_i$, or the ratio of Chinese imports from the United States to Chinese total imports of commodity i, accounts for the features of China's import demand function ($M^{*'}_i$ in theoretical equation 5). While this term does not offer a straightforward interpretation because of its complicated relationship with the theoretical expression, we can reasonably anticipate that the United States offered larger production subsidies to commodities for which China's demand for US products was comparatively high prior to the trade war.

To capture the dependency between subsidy rates and tariff rates, equation (8) includes the US Section 301 and Chinese retaliatory tariff rates for each commodity (t^u_i and t^c_i). We anticipate that subsidization rates are higher for commodities that faced larger retaliatory tariffs from China during the dispute, though, as described earlier, it was also the case that many commodities received government support despite being largely unaffected by China's retaliatory response.[14] As in the tariff equations, we also include a set of BEC indicator variables to account for industry features.[15] Finally, the error term for the subsidy equation is given by ν^u_i.

As detailed above, the US Section 301 tariffs were enacted in four sequential phases, with each phase of US tariffs met contemporaneously by Chinese retaliatory tariffs. These tariffs include those enacted in July 2018 (List 1), August 2018 (List 2), September 2018 (List 3), and September 2019 (List 4a). We do not include List 4b tariffs, because they were scheduled to take effect in December 2019 but were suspended with the negotiation of the Phase One deal. We compile data on these tariffs based on the announcements made by the USTR and the Chinese MOC, which detail the targeted 8-digit (and sometimes 10-digit) commodities. These lists include 10,747 products at the 8- or 10-digit levels targeted by the United States and 7,685 products by China. However, because each

[13] The BEC variables span the complete set of BEC sectors (i.e., no category is omitted). The seven top-level BEC categories include BEC-1: Food and beverages; BEC-2: Industrial supplies not elsewhere specified; BEC-3: Fuels and lubricants; BEC-4: Capital goods (excluding transport equipment); BEC-5: Transport equipment and parts and accessories thereof; BEC-6: Consumer goods not elsewhere specified; BEC-7: Goods not elsewhere specified. In order to include indicators for the full set of BEC classifications, we omit the intercept from each specification.

[14] We implicitly assume that t^u_i and t^c_i are exogenous in equation (8). This is a reasonable assumption because the MFP payments were announced and implemented after the retaliatory tariffs had already been enacted rather than being developed and implemented along with the announced tariff schedules; thus, it is unlikely that the retaliatory tariff rates were simultaneously determined with subsidy rates.

[15] Because US subsidies under MFP were provided exclusively for agricultural products, equation (8) is estimated by including only observations corresponding to food and agricultural products (6-digit commodities under HS chapters 02–24 and 52); we are therefore able to include indicators for BEC categories 1 and 2 (food and beverages and industrial supplies not elsewhere specified) only in the US subsidy specification.

Table 1. Imputed *Ad Valorem* MFP Subsidy Rates (percentage)

Commodity	MFP 2018 Rate	MFP 2019 Rate	Commodity	MFP 2018 Rate	MFP 2019 Rate
Alfalfa hay		4.1	Mustard seed*		9.5
Almonds*	0.7	0.5	Oats*		52.8
Barley*		7.8	Peanuts*		13.0
Beans, dry*		8.9	Peas, dry*		15.0
Canola*		7.0	Pecans		9.5
Cherries	17.4	16.6	Pistachios		0.9
Chickpeas*		8.0	Rapeseed*		6.8
Corn*	0.4	9.8	Rice*		7.3
Cotton*	9.0	22.1	Rye*		68.2
Cranberries		12.3	Safflower*		6.3
Dairy	0.7	0.9	Sesame seed*		7.0
Flaxseed*		14.9	Sorghum*	26.4	25.6
Grapes		0.9	Soybeans*	19.4	15.4
Hazelnuts		5.4	Sunflower*		10.7
Hogs	3.1	3.9	Triticale*		18.8
Lentils		8.9	Walnuts		1.2
Macadamia nuts		2.2	Wheat*	2.5	18.8
Millet*		34.9			

Notes: Authors' calculations based on USDA announcements, Farm Service Agency (FSA) acreage data, and FAO production data. A single asterisk (*) indicates commodities for which MFP 2019 payments were allocated at county-specific rates. Blank entries indicate that the commodity was ineligible for 2018 MFP payments.

country maintains its own unique commodity nomenclature at the 8- and 10-digit levels, we truncate the commodity definition at the 6-digit HS level to ensure the comparability of the commodity definitions across the two datasets.[16] With these truncations, our tariff data reflect duties imposed on a cumulative 5,197 products (the sum of the number of tariffed products under Lists 1–4a) at the 6-digit level targeted by the United States and 4,899 such products targeted by China.

The USDA determined MFP payment rates across commodities based on the expected losses in gross export sales resulting from tariff retaliation by China and other countries targeted by US trade actions during the trade war period. The estimated export sales losses were then divided by the total US value of production to generate an estimate of trade damages per unit of production, the value of which provided the direct basis for the payment rates under MFP 2018 (Glauber, 2021). To translate these payment rates into *ad valorem* equivalent subsidy rates by commodity, we use the original MFP payment rate schedules announced by the USDA.[17]

[16] For example, China imposed 25% *ad valorem* tariffs on imports of yellow soybeans (recorded under commodity code 12019010) and black soybeans (commodity 12019020) from the United States, each of which reflect commodity definitions specific to trade statistics compiled by China's MOC. We thus truncate the commodity definition in this case to 120190 (soybeans) to maintain comparability between the two countries' announcements and with the universal HS commodity classification.

[17] Because export values were based on predicted (rather than observed) trade losses, some commodity groups were overcompensated by MFP in cases where expected export losses far exceeded realized export losses (Janzen and Hendricks, 2020). Cotton producers in particular benefited disproportionately from MFP because US cotton prices and exports during the trade war period declined far less than the USDA's projections had predicted (Ridley and Devadoss, 2023). Changes in the approach to calculating MFP payment rates between the 2018 and 2019 versions of the program also provided a windfall for cotton producers. Because the base years (2010–2012) used in the USDA's projections of trade losses reflected a period of record-high US–China cotton exports, the projections on trade-war-induced export losses yielded payment rates for cotton producers that dramatically exceeded the realized extent of the trade damages.

The first installment of subsidy payments (2018 MFP) roughly coincided with the List 1–3 tariff announcements: The initial announcement establishing the MFP payments occurred in July 2018, and the eligible list of commodities was finalized in September 2018. Payment rates for the 2018 MFP were calculated on a per unit basis that varied by commodity, with a total of nine commodities (dairy, hogs, corn, sorghum, wheat, cotton, cherries, soybeans, and almonds) being eligible for the payments. The second tranche of MFP payments (2019 MFP) was announced in May 2019, roughly coinciding with an announcement by Chinese authorities of their intentions to raise tariffs on many of the commodities included in the September 2018 List 3. In 2019 MFP, the list of eligible commodities was expanded to 37 products, extending eligibility to producers of many specialty crops (grapes, cranberries, several types of nuts), other oilseeds besides soybeans, and a wide assortment of other commodities, including rice, beans, and barley. Strikingly, many of the commodities eligible for MFP payments (e.g., corn, wheat, and several others) did not incur significant trade losses at any point during the dispute, owing to negligible existing trade between the United States and China in such commodities.[18, 19] The *ad valorem* subsidy rates computed based on these three approaches for the 2018 and 2019 tranches of MFP payments are presented in Table 1, which illustrates significant differences in the effective rates of support provided to producers of various commodities.[20]

We estimate equations (6)–(8) using several approaches to account for specific features of the underlying data-generating process for each. Our baseline results are obtained by estimating each equation separately via ordinary least squares (OLS). This corresponds to a linear probability model (LPM) in the binary analysis of US tariff coverage. However, to account for the discreteness of the dependent variable in this analysis and the fact that probabilities are bounded between 0 and 1, we also estimate a logit model for this relationship.[21] For the Chinese tariff and US MFP specifications, we additionally employ a Poisson pseudo-maximum likelihood (PPML) regression approach to account for the fact that the tariff and subsidy rates are bounded from below at 0 as well as the presence of a significant number of zeros in the data.[22] Specifically (and particularly in List 1–3), many commodities faced no additional tariffs as part of the dispute (t_i^u or t_i^c is 0), and comparatively few commodities received subsidies (s_i^u is often 0, even when focusing solely on agricultural products).

To capture the timing of the tariff and subsidy actions and, importantly, the notion that political and/or economic incentives might have played roles of evolving importance at various junctures of the dispute, we estimate equations (6)–(8) separately for all the commodities targeted under the List 1–3 tariffs (the set of tariffs enacted during mid-2018) versus the tariff rates of all the commodities targeted under List 1–4a (those enacted over the entire duration of the dispute). Because the MFP payment rates were set in late 2018 and mid-2019, roughly contemporaneously with the List 1–3 tariffs, we model subsidy rates as a function of the cumulative List 1–3 tariff rates.

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[18] Rye and millet provide other noteworthy examples, which per our calculations received subsidy rates of 68.2% and 34.9%, respectively, under MFP 2019. The United States does not export any rye to China, and China only accounted for around $556,000 of US millet exports, or 1% of total US millet exports. These commodities were also mostly spared from significant trade damages under other countries' retaliatory responses to the US Section 201 and Section 232 trade actions.

[19] Because MFP payments were calculated based on (i) a per unit basis for some commodities, (ii) a per head basis for livestock, and (iii) a per acre basis for other commodities, we compute the subsidy rate separately for each case. Further detail on our calculation of MFP payment rates is provided in the online supplement.

[20] We exclude two commodities eligible for MFP 2019 payments (crambe and ginseng) from our analysis because there is no readily available data on production for these commodities.

[21] Employing a probit model, we obtain effectively identical estimates.

[22] Ours is a Poisson *pseudo*-maximum likelihood estimator because tariff rates are a continuous variable rather than a count variable, as in a formal Poisson estimation. Poisson estimators are generally consistent estimators of conditional means even when the underlying Poisson distributional assumption does not hold and maintain desirable properties in addition to their capacity to handle data with large numbers of zeros; see Santos Silva and Tenreyro (2011) or Verdier (2016).

Table 2. Theoretical Variables, Empirical Counterparts, and Data Sources

Variable	Empirical Counterpart	Data Source
τ_i, τ_i^*	*Ad valorem* tariff rates	USTR/China MOC announcements
σ_i	*Ad valorem* subsidy rates	USDA/Glauber (2021)/authors' calculation
I_{iL}, α_L	Red-state share	BEA; authors' calculation
b_i^*	SOE share	Chinese National Bureau of Statistics
M_i	Net exports from US to China	CEPII's BACI
X_i, X_i^*	Total exports	CEPII's BACI
$M_i', M_i^{*'}$	Bilateral import/export shares	CEPII's BACI
$\varepsilon_i, \varepsilon_i^*$	Elasticities of export supply	CEPII's BACI; Soderberry's (2015) methodology

Table 2 summarizes the correspondence between the key components of the theoretical model, their empirical counterparts, and the data sources.[23, 24]

Econometric Results

Table 3 reports the results for the commodities targeted by US tariffs as described in equation (6). The estimates obtained under the LPM versus logit estimations are depicted in columns (1) and (2) for the List 1–3 tariffs and columns (3) and (4) for the List 1–4a tariffs. Because the results from the two estimators are largely the same in sign and significance, we focus on the discussion of the LPM results.

The estimates for both sets of tariffs (List 1–3 vs. List 1–4a) largely confirm the predictions of the theoretical model. As seen by the large and positive estimates on *Red-state share* (roughly 0.230 and 0.063, respectively, for the List 1–3 and List 1–4a estimates), the tariffs imposed by the United States were most extensively applied on imported commodities, for which US production is predominantly located in Republican-voting states. Specifically, the estimates imply that a 1-percentage-point change in *Red-state share* corresponds on average to respective increases of 0.230 and 0.063 percentage points in the probability that a product was included in the US List 1–3 or List 1–4a tariffs on Chinese imports. To illustrate the interpretation of this finding, the estimate implies that, *ceteris paribus*, products in an industry like primary metal manufacturing (with a red-state share of 81%) were 11.3% more likely to be targeted under the List 1–3 tariffs than products in an industry like apparel manufacturing (with a red-state share of 32%) ($0.113 = 0.230 \times [81 - 32]$). This result aligns with the prediction from the analytical framework that tariff actions were shaped by policymakers in support of banking votes to secure reelection. Surprisingly, we find that the point estimates on X^u are insignificant for the List 1–3 tariffs and significantly negative for the List 1–4a tariffs. This suggests that industry size had little bearing on the initial rounds of US tariffs and that products in larger US industries (i.e., industries with higher exports) were less likely to be targeted by tariffs under the List 1–4a actions. Higher import shares were associated with a higher probability of a product being tariffed during the first part of the dispute (likely indicative of US policymakers' focus on retaliating against products imported in large volumes, such as electronic equipment, apparel, and footwear), though this effect becomes negative when considering the entire set of List 1–4a tariff rates. A conceivable explanation for this finding is that the initial rounds of US tariffs in List 1–3 targeted products that were extensively imported from China, but by the introduction of the more-comprehensive List 4a tariffs, the scope of the duties had expanded to include even commodities for which China is not a major source of imports. Finally, the optimal tariff/market-power term is positive

[23] The online supplement presents summary statistics on the empirical variables.

[24] We also undertake an analysis of US Section 301 tariffs and MFP subsidies to ascertain whether the electoral geography of industries gave rise to differential impacts for the other economic and sectoral covariates in our model. The results of this analysis are presented in the online supplement along with corresponding discussion.

Table 3. Determinants of US Section 301 Tariffs (N = 5,228)

	List 1–3 (3,746 targeted products)		List 1–4a (4,973 targeted products)	
	LPM	Logit	LPM	Logit
	1	2	3	4
Red-state share	0.230***	1.354***	0.063**	2.457***
	(0.057)	(0.325)	(0.028)	(0.552)
X^u	0.000	0.000	−0.006***	−0.094***
	(0.001)	(0.010)	(0.001)	(0.017)
Import share	0.062**	0.363**	−0.151***	−2.904***
	(0.026)	(0.160)	(0.020)	(0.255)
$1/\varepsilon^c$	0.040***	3.126***	0.008***	0.794
	(0.010)	(0.715)	(0.003)	(0.822)
t^u_{MFN}	0.002***	0.012**	0.001	2.134***
	0.000	(0.005)	(0.001)	(0.277)
BEC sectors				
Food and beverages	0.477***	−0.380*	0.980***	5.506***
	(0.036)	(0.195)	(0.017)	(1.052)
Industrial supplies n.e.s.	0.639***	0.405*	0.941***	1.614***
	(0.038)	(0.212)	(0.021)	(0.442)
Fuels and lubricants	0.824***	13.898***	1.035***	16.243***
	(0.044)	(0.336)	(0.029)	(0.742)
Capital goods and parts	0.707***	0.844***	0.985***	3.455***
	(0.035)	(0.210)	(0.019)	(0.467)
Transport equipment	0.758***	1.534***	1.037***	5.006***
	(0.046)	(0.401)	(0.029)	(1.409)
Consumer goods n.e.s.	0.152***	−1.781***	0.910***	1.297***
	(0.030)	(0.177)	(0.016)	(0.377)
Other goods n.e.s.	0.127	−1.867***	0.971***	15.124***
	(0.110)	(0.556)	(0.019)	(0.444)
R^2	0.768		0.955	
Log-likelihood		−2,653.0		−795.6

Notes: The dependent variable is an indicator variable reflecting whether a 6-digit commodity was targeted by US Section 301 tariffs on Chinese imports. Robust standard errors are reported in parentheses. Intercept is excluded from the regression. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% levels, respectively.

and significant in all but one of the specifications, which captures the incentives for policymakers to maintain higher tariffs on commodities for which China's export supply is relatively inelastic (i.e., for which $1/\varepsilon^c$ is high). This result suggests that the United States would gain from the terms-of-trade effects of depressing the import prices of Chinese goods. As evident from the estimate on MFN tariff rates (t^u_{MFN}), the US duties tended to be higher on products that already faced high tariffs.

We briefly discuss the results on the BEC sector indicators and, in particular, how these estimates illustrate the evolution of the US Section 301 tariffs over the course of the dispute.[25] The initial focus of US tariffs was primarily on capital goods and transport equipment as evident from the sizable coefficients on the associated variables. Imports of consumer goods and, to a lesser extent, food products faced noticeably lower US Section 301 tariffs. This finding corresponds to the notion that the Trump administration generally avoided implementing duties on such imports, as tariffs on household goods would have had acute impacts on voters.

[25] The outsize estimates on the BEC indicators for "fuels and lubricants" under List 1–3 and "fuels and lubricants" and "other goods not elsewhere specified" under List 1–4a reflect that nearly all products under these categories were tariffed under these actions.

Next, we discuss the results on the determinants of China's retaliatory tariffs (Table 4). We focus on the OLS results due to their qualitative similarity to the PPML results.[26] We find clear evidence that industry size and political economy factors (as captured by the estimates on X^c and SOE share) typically led China to impose higher retaliatory tariff rates. There is a consistent negative relationship between higher import shares of US products in China and the size of the retaliatory tariff rates, which contrasts with the results on the US tariff analysis. While the most visible Chinese tariffs (for instance, those on US soybeans and pork) targeted products for which the United States is a key source for China's imports, the prevailing general theme was that Chinese policymakers strategically refrained from enacting high tariff rates on commodities for which the United States is a key supplier. This contrast in approaches between US and Chinese policymakers is not surprising; commentators frequently appraised the US tariff efforts as ad hoc and capricious (Bown, Jung, and Lu, 2018b) because they were enacted with limited consideration of the profound negative impacts of these duties on products for which China is the major supplier. As in the US tariff analysis, there is also a strong and positive relationship between the tariff rates and the inverse elasticity of US export supply. As was seen in the US tariff analysis, we find that China imposed higher duties on commodities for which it had already maintained high MFN tariff rates (t^c_{MFN}) before the trade dispute.

Like their analogs in the US tariff results, the estimates on products' BEC categories illustrate the scope of China's retaliatory tariffs across different broad industrial groupings. Consistent with the front-and-center role played by many US agricultural products in the dispute, we find that China's tariffs on food and beverages tended to be higher in magnitude than its tariffs on other products. Furthermore, imports of fuels and lubricants as well as capital goods and parts also faced systematically high retaliatory tariffs during the dispute. Of further note is that, *ceteris paribus*, the variables for the BEC categories almost uniformly generate smaller estimates than their counterparts for the US tariff estimates, consistent with the idea that policy makers in the nondemocratic country face fewer incentives to enact high tariffs owing to the lack of electoral considerations in their objective functions.

Last, we explore the factors that influenced the US government's provision of MFP subsidies to the US agricultural sector (Table 5). As elaborated above, the subsidy analysis only considers food and agricultural products, as MFP was confined to such commodities. MFP 2018 payments were positively correlated with US Section 301 tariff rates. In contrast, and perhaps surprisingly, the level of the subsidy rates was generally negatively correlated with the magnitude of China's retaliatory tariff rates, significantly so for MFP 2019. A closer examination of China's retaliatory tariffs on US agricultural products helps rationalize this finding.

Specifically, and as seen in Table 1, several commodities (in particular, most cereal grains and several oilseeds) benefited from significantly higher payment rates than other products (e.g., most specialty crops). Some prominent products (e.g., pork and soybeans) that faced large and disruptive Chinese tariffs received high subsidies. In contrast, many other agricultural products (e.g., millet, oats, and rye) faced low tariffs but still received high subsidy rates. There were also commodities (almonds, grapes, and pistachios) that endured large tariffs but received no or small subsidies. To illustrate, the highest Chinese tariffs enacted over the entire dispute on US exports of millet, oats, and rye reached only 10%, but producers of these commodities received subsidies ranging from 34.9% to 68.2%. In contrast, US exports of almonds, grapes, and pistachios faced 25% tariffs from the dispute's outset, but producers of these goods received negligible government support. Notably, these commodities are largely grown in Democratic-voting states.

[26] To illustrate with an example, the OLS estimate on the Chinese List 1 –3 tariffs for the "food and beverages" BEC indicator variable is equal to 16.178 (column 1). This estimate implies that Chinese tariffs in this sector were on average 16.178 percentage points higher than in other sectors, conditional on the other controls. The corresponding PPML estimate is 2.794, which, when exponentiated, implies that tariff rates for this BEC sector were on average 16.346 percentage points higher, *ceteris paribus*. The extremely close relationship between most of the results obtained by the two estimators therefore suggests that our OLS estimates are not observably biased by the prevalence of 0 observations. In the context of gravity model estimation, Santos Silva and Tenreyro's (2006) seminal analysis arrives at a similar conclusion regarding minimal bias attributable to the prevalence of 0 observations in OLS versus PPML estimations.

Table 4. Determinants of China's Tariffs on Imports from the United States (N = 5,320)

	List 1–3 (4,226 targeted products)		List 1–4a (4,462 targeted products)	
	OLS	**PPML**	**OLS**	**PPML**
	1	**2**	**3**	**4**
SOE share	6.507***	0.377***	5.406***	0.308***
	(1.304)	(0.074)	(1.267)	(0.071)
X^c	0.039***	0.002***	0.036***	0.002***
	(0.008)	0.000	(0.008)	(0.000)
Import share	−8.730***	−0.631***	−8.707***	−0.612***
	(0.758)	(0.064)	(0.722)	(0.059)
$1/\varepsilon^u$	0.151***	0.008***	0.147***	0.008***
	(0.055)	(0.002)	(0.054)	(0.002)
t^*_{MFN}	0.563*	0.029**	0.625**	0.031***
	(0.325)	(0.013)	(0.297)	(0.011)
BEC sectors				
Food and beverages	16.178***	2.794***	17.188***	2.855***
	(0.640)	(0.031)	(0.579)	(0.027)
Industrial supplies n.e.s.	15.006***	2.722***	15.492***	2.753***
	(0.403)	(0.021)	(0.377)	(0.019)
Fuels and lubricants	18.153***	2.882***	18.845***	2.925***
	(1.949)	(0.099)	(1.871)	(0.094)
Capital goods and parts	17.634***	2.884***	17.756***	2.891***
	(0.426)	(0.021)	(0.408)	(0.020)
Transport equipment	11.135***	2.478***	11.494***	2.502***
	(1.032)	(0.068)	(1.004)	(0.067)
Consumer goods n.e.s.	17.269***	2.860***	17.364***	2.867***
	(0.625)	(0.029)	(0.585)	(0.026)
Other goods n.e.s.	3.753**	1.416***	3.842**	1.422***
	(1.753)	(0.411)	(1.754)	(0.411)
R^2	0.731		0.757	
Pseudo log-likelihood		−34,915.5		−32,209.3

Notes: The dependent variable is China's *ad valorem* retaliatory tariff rate on imports from the United States by commodity, t_i^c, cumulative across the indicated lists. Robust standard errors are reported in parentheses. Intercept is excluded from the regression. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% levels, respectively.

It is therefore apparent (though counterintuitive) that the program, with some exceptions, offered higher subsidies to commodities that did not suffer from high retaliatory duties and lower payment rates to commodities that did. This finding illustrates two key points. First, it clearly highlights how the theoretical model's predictions are consistent with the observed policy outcomes (i.e., that politically connected commodities and regions often benefited from higher levels of government support). Second, and relatedly, it illustrates how disbursements of the MFP payments, ostensibly enacted to mitigate trade losses incurred by US farmers, were often allocated in a way that belied the program's stated rationale.

It is also evident that political factors played a key role in the determination of subsidy rates within the two batches of MFP payments. The *Red-state share* estimate is positive and significant, and the effect nearly tripled in size between MFP 2018 and MFP 2019. This suggests that both the scope and magnitude of the MFP payments were underpinned by electoral considerations and that the role of these motives intensified as the dispute progressed. We also find support for the prediction that sectors with larger export volumes as well as commodities with higher exports to China (the estimates on X^u and M, respectively) typically received higher subsidy rates. Consistent with the theoretical predictions, US policy makers assign higher priority to subsidizing economically prominent sectors, which are likely to be the ones possessing more political clout. And in line with the underlying motivation for the ad hoc program's creation, MFP subsidy rates were on average higher for commodities for which the Chinese market is an important destination for US exports (though with notable exceptions, such as corn and wheat); specifically, a $1 billion increase in bilateral net US exports to China was associated with a 5.4- and 4.4-percentage point increase in the subsidy rate across MFP 2018 and MFP 2019, respectively.

In sum, our findings from estimating the empirical relationships in equations (6)–(8) largely confirm the key predictions from their theoretical counterparts in equations (4), (4*), and (5). As anticipated, our results suggest that the US Section 301 tariffs enacted during both the initial and later junctures of the dispute were consistent with US policymakers weighing both political and economic factors. Our findings also suggest that Chinese policymakers similarly implemented their tariff response in a manner consistent with favoring politically connected industries, as measured by the extent of government ownership within particular sectors. Particularly revealing are the findings on the US MFP subsidy rates. The estimates support the notion that political concerns were a key driver of the subsidy program, and that much of the ostensible rationale (mitigating the impacts of high tariffs on major US export commodities) for the program's creation was belied by the observed allocation of the payments.

Our results corroborate related findings from several related works in the literature. For instance, Janzen and Hendricks (2020) describe that MFP payments were often allocated in a way that overcompensated for realized trade damages. This aligns with our result on the weak link between the level of China's retaliatory tariff rates and the magnitude of MFP support for various commodities. Our findings are also consistent with that documented by Choi and Lim (2023) with respect to the disproportionate disbursement of MFP payments to Republican-voting US counties. Janzen et al. (2023) also document that MFP payments in 2018–2019 were correlated with higher Republican vote shares in the 2020 election.

It is important to highlight, however, the way in which our findings depart from existing related work. In particular, we again emphasize that the large majority of analyses on the political implications of the US–China trade war, such as those cited above, examine its *ex post* impacts. Our findings are therefore unique in that they describe the evolution of tariff and subsidy policy in *ex ante* terms (i.e., by elucidating the origins of these policies rather than their impacts).

Conclusion

The recent trade dispute between the United States and China was the largest of its kind in modern history, with the protracted back-and-forth counterpunches between the two economic superpowers causing significant and enduring disruptions to the world's largest bilateral trading relationship. The conflict encompassed many fronts reflecting a myriad of US grievances over China's trade and investment practices, industrial policies, and national security and import safeguard concerns, among other issues. However, the tariffs enacted as part of the US Section 301 complaint (along with the resulting Chinese retaliation) were far-reaching and seismic in their impact on many segments of the US economy (particularly US agriculture). In response to China's retaliatory tariffs, which extensively targeted US exports of agricultural products, the United States enacted the enormous ad hoc MFP payments to compensate US farmers for lost export revenues, a major subsidization effort without comparable antecedent. And while the two countries were able to negotiate a truce in the conflict via the Phase One deal in early 2020, many of the duties enacted by both sides have remained in place to date, indicative of the contentious nature of the dispute.

In this study, we explore the political and economic determinants of the tariff and subsidy policy actions undertaken during the US–China trade war by conducting both theoretical and empirical analyses. In particular, we show that political considerations (as measured by the electoral geography of the production of tariff-targeted commodities) were a key determinant of US tariff and subsidy

Table 5. Determinants of US MFP Subsidies (N = 1,000)

	MFP 2018		MFP 2019	
	OLS	**PPML**	**OLS**	**PPML**
	1	**2**	**3**	**4**
t^u	0.009*	0.032	0.016	0.011
	(0.004)	(0.022)	(0.013)	(0.015)
t^c	−0.002	0.012	−0.040**	−0.034**
	(0.007)	(0.030)	(0.018)	(0.015)
Red-state share	1.960***	18.668***	5.447***	6.608**
	(0.673)	(6.451)	(1.592)	(2.871)
X^u	0.162	0.241***	0.365***	0.154***
	(0.142)	(0.077)	(0.118)	(0.030)
M	5.355***	0.222	4.352**	0.254
	(1.347)	(0.323)	(2.214)	(0.200)
Import share	0.514	2.608***	0.603	0.798
	(0.541)	(0.912)	(0.790)	(0.567)
BEC sectors				
Food and beverages	−1.231***	−14.464***	−2.177**	−3.885**
	(0.429)	(3.894)	(1.026)	(1.766)
Industrial supplies n.e.s.	−1.402***	−15.884***	−2.543*	−4.376*
	(0.513)	(4.753)	(1.303)	(2.261)
R^2	0.242		0.077	
Pseudo log-likelihood		−574.3		−2,749.0

Notes: The dependent variable is the *ad valorem* US subsidy payment rate by commodity, s_i^u, for MFP 2018 and MFP 2019, respectively. Observations include food and agricultural commodities (HS chapters 02–24 and 52). Robust standard errors are reported in parentheses. Intercept is excluded from the regression. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% levels, respectively.

actions, while economic considerations (e.g., optimal tariff relationships, attributes of the export supply and import demand functions, and trade balances) were also important factors. The size and scope of China's tariff retaliation was also consistent with enacting higher levels of protectionism in larger sectors with extensive state ownership.

While numerous studies have conducted *ex post* assessments of the US–China trade war's impacts on various economic outcomes, both within and beyond the agricultural sector, ours is the first (to our knowledge) to both theoretically and empirically the ways in which various political and economic factors underpinned the evolution of the policy actions undertaken during the dispute. Further, and in light of the outsize role played by the agricultural sector in the dispute, our study contributes to the impact analyses by a large number of studies by providing theoretical and empirical explanations of the dispute's evolution and continuation.

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Online Supplement: Determinants of Policy Responses in the US-China Tit-for-Tat Trade War

William Ridley and Stephen Devadoss

Calculation of MFP Subsidy Rates

To calculate ad valorem subsidy rates for commodities that received MFP payments on a per-unit basis, we multiply the commodity-level total quantity of US production in the respective program years (2018 versus 2019) by the relevant per-unit subsidy rate, and then divide this figure by the total dollar value of the commodity's annual US production for the respective years to obtain effective subsidy rates. To incorporate ad valorem support rates for livestock (payments for which were offered in per-head terms), we adopt the relevant calculations from Glauber (2021), who computes effective ad valorem subsidy rates for the relevant MFP-targeted animal products.

However, for a large number of commodities (such as corn, soybeans, cotton, wheat, and others), many payment rates for MFP 2019 were defined commonly at the US-county level rather than in per-unit terms specific to the individual commodities.[1] Computation of the subsidy rates for these commodities proceeds as follows. For 2019, we obtain the planted acreage for each of these commodities in each US county (data from the USDA Farm Service Agency (FSA)) and multiply this acreage by the county-specific MFP 2019 per-acre rate to obtain total payments per county, per commodity. Then we sum the payments to all counties for each commodity to obtain the US total MFP payments for that commodity. These values are then divided by the total 2019 value of US production of the corresponding commodity to obtain ad valorem subsidy rates.

A final consideration in computing subsidy rates involves matching the broad MFP commodities to HS commodity definitions so that our subsidy analysis is comparable in its commodity dimension to our tariff analysis. Specifically, MFP payments were in some instances provided to producers of primary products to mitigate trade losses from tariffs on processed commodities (for example, support payments for hog farmers to mitigate export losses in pork products, or support for dairy operations to mitigate trade losses in dairy products). To this end, we manually match each MFP commodity to one or more 6-digit HS code corresponding to the relevant traded commodities, which primarily entails the matching of the per-head subsidy rates for hogs and dairy cows to the relevant traded animal products. Table S1 presents the matching between the broad MFP commodity definitions and the HS commodity codes. Many commodities (such as alfalfa hay or canola) can be matched one-to-one with a particular HS code, whereas other commodities are matched on a one-to-many basis; for instance, "Beans, dry" encompasses multiple 6-digit HS commodities. However, in general there is a reasonably exact correspondence between the MFP commodity definitions and the traded commodity definitions.

[1] That is, payment rates for some commodities were determined at a common rate specific to the producer's location, calculated based on historical production and yield information. For example, a soybean grower in Story County, Iowa would have been eligible for payments of $64 per acre of eligible production under MFP 2019, while a soybean producer in neighboring Polk County would have been eligible for a payment rate of $69 per acre. The same per-acre payment rate applies to other crops that came under per-acre payment rates and grown in that county.

Table S1. MFP Commodities and Corresponding HS Commodity Codes

MFP Commodity	HS Commodity	HS Code	MFP Commodity	HS Commodity	HS Code
Alfalfa hay	Alfalfa hay	121410	Grapes	Grapes	0806xx
Almonds	Almonds	0802xx	Hazelnuts	Hazelnuts	0802xx
Barley	Barley	1003xx	Hogs	Meat of swine	0203xx
Beans, dry	Beans, mung	071331	Lentils	Lentils	071340
	Beans, small red	071332	Macadamia nuts	Macadamia nuts	0802xx
	Beans, kidney	071333	Millet	Millet	1008xx
	Beans, n.e.s.	071339	Mustard seed	Mustard seed	120750
	Beans, broad	071350	Oats	Oats	1004xx
	Beans, other	071390	Peanuts	Peanuts	1202xx
Canola	Canola	120510	Peas, dry	Peas, dry	071310
Cherries	Cherries, sweet	080929	Pecans	Pecans	080290
Chickpeas	Chickpeas	071320	Pistachios	Pistachios	0802xx
Corn	Corn	1005xx	Rapeseed	Rapeseed	120590
Cotton	Cotton, not carded or combed	5201xx	Rice	Rice	1006xx
	Cotton, waste	5202xx	Rye	Rye	1002xx
	Cotton, carded and combed	5203xx	Safflower	Safflower	120760
Cranberries	Cranberries	081040	Sesame Seed	Sesame Seed	120740
Dairy	Milk and cream	0401xx	Sorghum	Sorghum	1007xx
	Milk and cream concentrated	0402xx	Soybeans	Soybeans	1201xx
	Buttermilk and yogurt	0403xx	Sunflower	Sunflower	1206xx
	Whey	0404xx	Triticale	Triticale	100860
	Butter	0405xx	Walnuts	Walnuts	0802xx
	Cheese	0406xx	Wheat	Wheat	1001xx
Flaxseed	Flaxseed	1204xx			

Notes: "xx" indicates that the commodity definition includes all 6-digit commodities within the indicated 4-digit grouping.

Summary Statistics

Table S2. Summary Statistics for Empirical Variables

Variable	Mean	Std. Dev.	Min.	Max.
$I\,(t^u > 0)$ (List 1–3)	0.72	0.45	0	1
$I\,(t^u > 0)$ (List 1–4a)	0.95	0.22	0	1
t^u_{MFN}	4.20	41.93	0	3,000
t^c (List 1–3)	16.30	10.25	0	25
t^c (List 1–4a)	16.67	9.81	0	25
t^c_{MFN}	9.79	9.72	0	408.84
s^u (MFP 2018)*	0.20	1.71	0	26.43
s^u (MFP 2019)*	0.96	5.06	0	68.22
Red-state share	0.61	0.12	0.32	0.89
SOE share	0.12	0.12	0.01	0.99
M	0	0.12	–0.35	3.58
X^u	1.95	5.43	0	55.68
X^c	3.67	13.48	0	284.08
Imp. share^{u,c}	0.20	0.24	0	1
Imp. share^{c,u}	0.11	0.18	0	1
$1/\varepsilon^u$	2.29	16.74	0	482.90
$1/\varepsilon^c$	2.95	28.88	0	1,012.48

Notes: All variables are defined at the commodity level. * The summary statistics for the MFP payments are computed only across commodities in food and agriculture (HS chapters 02–24 and 52). M (bilateral net exports of the United States to China), X^u, and X^c (total exports by 4-digit HS commodity of the United States and China, respectively) are measured for 2017 in billion USD.

Red-State Production Shares by NAICS Industry

Table S3 presents the red-state production share variable for each of the 3-digit (and 3-digit aggregate) industries in the analysis, computed using BEA state- and sector-level GDP data for the year 2017.

Table S3. Red-State Production Shares by NAICS Industry

NAICS	Description	Red-State Share (%)
111–112	Farms	60.1
113–115	Forestry, fishing, and related activities	46.3
211	Oil and gas extraction	88.6
212	Mining (except oil and gas)	71.0
311–312	Food and beverage and tobacco product manufacturing	60.3
313–314	Textile mills and textile product mills	73.1
315–316	Apparel, leather, and allied product manufacturing	32.2
321	Wood product manufacturing	69.5
322	Paper manufacturing	73.5
323	Printing and related support activities	56.8
324	Petroleum and coal products manufacturing	68.2
325	Chemical manufacturing	59.7
326	Plastics and rubber products manufacturing	67.2
327	Nonmetallic mineral product manufacturing	65.7
331	Primary metal manufacturing	81.1
332	Fabricated metal product manufacturing	62.6
333	Machinery manufacturing	64.4
334	Computer and electronic product manufacturing	34.0
335	Electrical equipment, appliance, and component manufacturing	67.9
336	Transportation Equipment Manufacturing	70.2
337	Furniture and related product manufacturing	67.6
339	Miscellaneous manufacturing	44.7

Notes: “Red-state share” measures the share of US GDP for the respective industries accounted for by states voting Republican in the 2016 presidential election. Authors’ calculation using BEA data.

SOE Shares by ISIC Industry

Table S4 presents the SOE share variable for the 2-digit ISIC (Revision 4) industries in our analysis, computed using data for the year 2017 from the China Statistical Yearbook from China's National Bureau of Statistics. "SOE share" measures the share of revenues within each industry accounted for by government-owned firms. Because the Statistical Yearbook does not report SOE revenues individually for the agriculture, animal production, forestry, or fishing sectors, we take estimates of these values from the World Bank report by Zhang (2019).

To map 6-digit HS codes (the level of aggregation of the Chinese tariff data) to 2-digit ISIC codes, we use the HS to ISIC Revision 4 crosswalk produced by the OECD (2022).

Table S4. Share of Chinese SOEs in Industry Revenue by ISIC Industry

ISIC	Description	SOE share (%)	
01	Crop and animal production, hunting and related activities	6	6
02	Forestry and logging	6	6
03	Fishing and aquaculture	2	5
05	Mining of coal and lignite	64	1
06	Extraction of crude petroleum and natural gas	84	3
07	Mining of metal ores	44	0
08	Other mining and quarrying	8	8
10	Manufacture of food products	5	2
11	Manufacture of beverages	18	4
12	Manufacture of tobacco products	99	3
13	Manufacture of textiles	2	3
14	Manufacture of wearing apparel	1	0
15	Manufacture of leather and related products	0	7
16	Manufacture of wood and of products of wood and cork	1	6
17	Manufacture of paper and paper products	4	6
18	Printing and reproduction of recorded media	6	6
19	Manufacture of coke and refined petroleum products	56	2
20	Manufacture of chemicals and chemical products	17	5
21	Manufacture of pharmaceuticals	8	7
22	Manufacture of rubber and plastics products	3	8
23	Manufacture of other non-metallic mineral products	8	8
24	Manufacture of basic metals	34	3
25	Manufacture of fabricated metal products	6	9
26	Manufacture of computer, electronic and optical products	9	0
27	Manufacture of electrical equipment	8	8
28	Manufacture of machinery and equipment n.e.c.	11	0
29	Manufacture of motor vehicles, trailers and semi-trailers	43	8
30	Manufacture of other transport equipment	42	8
31	Manufacture of furniture	2	4
32	Other manufacturing	5	4
35	Electricity, gas, steam and air conditioning supply	87	4
38	Waste collection, treatment and disposal activities	4	7

Notes: "SOE share" measures the share of state-owned enterprises (SOEs) in Chinese industries' revenues at the 2-digit ISIC level for 2017. Authors' calculation using data from the 2018 China Statistical Yearbook produced by China's National Bureau of Statistics.

Estimating Elasticities of Export Supply

To estimate the elasticities of export supply at the product level for the United States and China, we follow the procedure of Soderberry (2015). This approach implements a limited information maximum likelihood (LIML) estimator to compute the elasticities of import demand and export supply based on the earlier framework of Feenstra (1994), later extended by Broda and Weinstein (2006). A system of import demand and export supply equations is given by

$$\text{(S1)} \qquad \Delta^k \ln s_{igvt} = -\left(\sigma_{ig} - 1\right) \Delta^k \ln p_{igvt} + \varepsilon^k_{igvt}$$

$$\text{(S2)} \qquad \Delta^k \ln p_{igvt} = \left(\frac{\omega_{ig}}{1 + \omega_{ig}}\right) \Delta^k \ln s_{igvt} + \delta^k_{igvt}.$$

s_{igvt} is the import share of variety v of good g in country i's imports, p_{igvt} is the price (unit value) of this variety in country i, σ_{ig} is country i's elasticity of import demand for good g, ω_{ig} is the inverse elasticity of export supply for good g, $\varepsilon^k_{igvt} = \varepsilon_{igvt} - \varepsilon_{igkt}$ is the difference in demand shocks ε between a particular variety v and a reference variety k, and $\delta^k_{igvt} = \delta_{igvt} - \delta_{igkt}$ is the difference between supply shocks δ between a particular variety v and a reference variety k. Δ^k is a "double-difference" operator that reflects the first difference in time for a variable, minus the first difference of the same variable for the reference variety k: $\Delta^k x_{igvt} = \Delta x_{igvt} - \Delta x_{igkt}$, where Δ is a simple first difference over time. As shown in Feenstra (1994), ε^k_{igvt} and δ^k_{igvt} can be multiplied together to convert the above equations into a single estimable equation:

$$\text{(S3)} \qquad Y_{igvt} = \theta_{1ig} X_{1igvt} + \theta_{2ig} X_{2igvt} + u_{igvt},$$

where $Y_{igvt} = \left(\Delta^k \ln p_{igvt}\right)^2$, $X_{1igvt} = \left(\Delta^k \ln s_{igvt}\right)^2$, $X_{2igvt} = \Delta^k \ln p_{igvt} \Delta^k \ln s_{igvt}$, and $u_{igvt} = \varepsilon^k_{igvt}\delta^k_{igvt}$. The parameters $\boldsymbol{\theta}_{ig} = \left(\theta_{1ig}, \theta_{2ig}\right)$ can be used to recover estimates of σ_{ig} and ω_{ig}, given that

$$\text{(S4)} \qquad \theta_{1ig} \equiv \frac{\omega_{ig}}{\left(1 + \omega_{ig}\right)\left(\sigma_{ig} - 1\right)} \quad \text{and} \quad \theta_{2ig} \equiv \frac{1 - \omega_{ig}\left(\sigma_{ig} - 2\right)}{\left(1 + \omega_{ig}\right)\left(\sigma_{ig} - 1\right)},$$

so long as the moment condition $\mathrm{E}\left(u_{igvt}\right) = \mathrm{E}\left(\varepsilon^k_{igvt}\delta^k_{igvt}\right) = 0$ holds, i.e., that the two-way differenced demand and supply shocks are uncorrelated with one another.

We estimate equation (S3) by LIML separately for each country (the United States and China) and each 4-digit HS heading to compute values of ω_{ig} and σ_{ig} (owing to data and computational limitations, it would be impractical to estimate the elasticity separately for each 6-digit HS commodity). When estimates of ω_{ig} and σ_{ig} fall outside of the feasible range (the theoretically consistent parameter space defined by $\omega_{ig} > 0$ and $\sigma_{ig} > 1$), we use a non-linear LIML routine constraining the estimates to the feasible parameter space.

We estimate these parameters at the 4-digit level using data on US and Chinese HS 6-digit product-level imports from all partners over the period 2007–2019. When the 4-digit elasticity cannot be estimated (generally, for commodities in which very little international trade takes place) because of data limitations, we assign the average estimated elasticity calculated based on the non-missing 4-digit elasticities from the same 2-digit HS chapter to the 4-digit category for which the elasticity cannot be computed. We present the averages for the inverse of the export supply elasticity for the United States and China by two-digit HS chapter (because it would be impractical to present each elasticity of export supply estimate at the 6-digit commodity level), given in Table S5. Just over half (104) of the 192 averages are greater then one, implying that export supply for products under the indicated chapters is inelastic on average. Some values of the inverse elasticity are particularly large (such as the inverse elasticity estimate of 42.41 for China's exports of HS chapter 38 –miscellaneous chemical products, or the estimated value of 51.65 for US exports of HS chapter 81 –other base metals), but these large values tend to manifest principally for commodities that are not extensively traded.

Table S5. Inverse Elasticity of Inverse Export Supply Estimates

	Mean $(1/\varepsilon^j)$			Mean $(1/\varepsilon^j)$	
HS chapter	**United States**	**China**	**HS chapter**	**United States**	**China**
01	1.11	0.86	49	1.97	2.11
02	0.61	0.63	50	1.03	0.68
03	0.54	0.65	51	2.46	0.30
04	3.01	0.91	52	0.71	1.79
05	0.49	0.43	53	0.72	0.51
06	0.98	1.96	54	1.34	1.40
07	14.19	0.26	55	0.48	1.97
08	0.33	1.54	56	1.33	1.13
09	0.16	0.83	57	2.01	0.56
10	0.42	0.05	58	1.41	1.16
11	1.98	0.10	59	1.39	1.25
12	0.41	0.44	60	0.50	0.34
13	0.02	0.00	61	3.08	0.67
14	0.58	0.06	62	2.51	1.41
15	0.56	0.28	63	2.25	0.72
16	3.04	18.35	64	0.09	2.96
17	0.10	1.79	65	13.25	10.58
18	4.63	0.51	66	11.20	0.66
19	0.22	0.28	67	7.76	0.04
20	0.30	0.47	68	0.92	1.12
21	6.61	2.42	69	1.10	1.22
22	1.38	0.46	70	1.85	0.30
23	0.21	0.05	71	7.33	0.37
24	0.51	0.10	72	1.53	0.89
25	1.49	1.44	73	1.41	0.40
26	1.27	0.18	74	4.35	0.85
27	0.38	0.28	75	1.95	3.44
28	1.08	0.74	76	1.18	1.03
29	1.03	3.45	78	0.19	2.07
30	1.14	2.66	79	0.54	1.39
31	0.04	0.78	80	0.49	0.44
32	1.50	0.18	81	51.65	0.83
33	1.75	2.75	82	3.13	1.57
34	2.14	0.91	83	2.58	2.43
35	0.68	10.81	84	2.07	2.96
36	1.22	1.04	85	2.42	2.33
37	8.35	3.71	86	0.31	2.88
38	1.70	42.41	87	1.00	0.65
39	1.18	3.38	88	0.66	36.15
40	1.14	7.29	89	17.15	0.47
41	2.84	0.36	90	1.88	4.55
42	1.49	5.46	91	3.66	2.17
43	3.46	0.48	92	1.93	0.07
44	0.43	11.00	93	0.60	0.59
45	0.74	0.59	94	2.95	0.81
46	0.08	0.34	95	0.46	1.06
47	1.01	0.19	96	2.23	2.77
48	2.29	3.23	97	3.20	0.45

Notes: Average of 4-digit inverse export supply elasticities obtained using the approach of Soderberry (2015). Trade data used in the estimation are for the years 2007 through 2019.

Results Using 6-Digit Exports to Proxy for Total Production

Tables S6–S8 present the results for the specifications where total exports (X^u and X^c) are measured at the 6-digit level, rather than the 4-digit level as in the main analysis. The estimates obtained from this alternative specification are qualitatively identical to those derived from the baseline specification.

Table S6. Determinants of US Section 301 Tariff with Total Exports Measured at 6-digit HS Level

	List 1–3				List 1–4a			
	LPM		Logit		LPM		Logit	
	(1)		(2)		(3)		(4)	
Red-state share	0.231***	(0.057)	1.372***	(0.326)	0.079***	(0.029)	2.920***	(0.500)
X^u (6-digit HS)	0.005	(0.004)	0.047	(0.041)	−0.008**	(0.004)	−0.084***	(0.031)
Import share	0.062**	(0.026)	0.374**	(0.160)	−0.143***	(0.021)	−2.671***	(0.265)
$1/\varepsilon^c$	0.039***	(0.010)	3.106***	(0.714)	0.006**	(0.002)	0.232	(0.405)
t^u_{MFN}	0.002***	(0.000)	0.012**	(0.005)	0.001	(0.001)	2.367***	(0.278)
BEC sectors								
Food and beverages	0.476***	(0.036)	−0.397**	(0.195)	0.966***	(0.017)	5.091***	(1.038)
Industrial supplies n.e.s.	0.638***	(0.038)	0.385*	(0.212)	0.924***	(0.022)	1.088***	(0.394)
Fuels and lubricants	0.818***	(0.043)	13.808***	(0.322)	0.967***	(0.024)	14.600***	(0.470)
Capital goods and parts	0.706***	(0.035)	0.812***	(0.208)	0.959***	(0.019)	2.501***	(0.355)
Transport equipment	0.755***	(0.043)	1.472***	(0.368)	0.958***	(0.024)	2.289***	(0.695)
Consumer goods n.e.s.	0.151***	(0.030)	−1.803***	(0.176)	0.892***	(0.017)	0.706**	(0.338)
Other goods n.e.s.	0.125	(0.111)	−1.897***	(0.558)	0.959***	(0.019)	14.635***	(0.412)
R^2	0.768				0.954			
Log-likelihood			−2,652.2				−825.6	
Targeted products	3,746		3,746		4,973		4,973	
Observations	5,228		5,228		5,228		5,228	

Notes: The dependent variable is an indicator variable reflecting whether a 6-digit commodity was targeted by US Section 301 tariffs on Chinese imports. Robust standard errors are reported in parentheses. Intercept is excluded from the regression. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% levels, respectively.

Table S7. Determinants of China's Tariffs on Imports from the United States with Total Exports Measured at 6-digit HS Level

	List 1–3				**List 1–4a**			
	OLS		PPML		OLS		PPML	
	(1)		**(2)**		**(3)**		**(4)**	
SOE share	6.437***	(1.303)	0.373***	(0.074)	5.345***	(1.265)	0.304***	(0.071)
X^c (6-digit HS)	0.178***	(0.063)	0.007***	(0.002)	0.173***	(0.060)	0.007***	(0.002)
Import share	−8.737***	(0.759)	−0.633***	(0.064)	−8.716***	(0.722)	−0.614***	(0.059)
$1/\varepsilon^u$	0.148***	(0.055)	0.008***	(0.002)	0.144***	(0.054)	0.007***	(0.002)
t^c_{MFN}	0.557*	(0.322)	0.029**	(0.013)	0.620**	(0.294)	0.031***	(0.011)
BEC sectors								
Food and beverages	16.214***	(0.637)	2.796***	(0.031)	17.220***	(0.576)	2.857***	(0.027)
Industrial supplies n.e.s.	15.054***	(0.400)	2.725***	(0.021)	15.534***	(0.374)	2.755***	(0.019)
Fuels and lubricants	18.165***	(1.954)	2.884***	(0.099)	18.852***	(1.875)	2.926***	(0.094)
Capital goods and parts	17.765***	(0.418)	2.893***	(0.021)	17.867***	(0.401)	2.899***	(0.020)
Transport equipment	11.305***	(1.026)	2.488***	(0.068)	11.645***	(0.999)	2.511***	(0.066)
Consumer goods n.e.s.	17.377***	(0.618)	2.866***	(0.028)	17.457***	(0.580)	2.873***	(0.026)
Other goods n.e.s.	3.765**	(1.751)	1.417***	(0.411)	3.853**	(1.752)	1.423***	(0.411)
R^2	0.732				0.757			
Pseudo log-likelihood			−34,908.4				−32,199.6	
Targeted products	4,226		4,226		4,462		4,462	
Observations	5,320		5,320		5,320		5,320	

Notes: The dependent variable is China's *ad valorem* retaliatory tariff rate on imports from the United States by commodity, t^c_i, cumulative across the indicated lists. Robust standard errors are reported in parentheses. Intercept is excluded from the regression. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% levels, respectively.

Table S8. Determinants of US MFP Subsidies with Total Exports Measured at 6-digit HS Level

	MFP 2018				**MFP 2019**			
	OLS		**PPML**		**OLS**		**PPML**	
	(1)		**(2)**		**(3)**		**(4)**	
t^u	0.008*	(0.004)	0.035*	(0.021)	0.014	(0.013)	0.011	(0.015)
t^c	0.001	(0.006)	0.016	(0.036)	−0.036**	(0.018)	−0.035**	(0.015)
Red-state share	1.823***	(0.649)	17.946***	(5.671)	5.123***	(1.597)	6.959**	(3.018)
X^u (6-digit HS)	−0.003	(0.157)	−0.045	(0.925)	0.623**	(0.295)	0.268***	(0.064)
M	6.135***	(1.614)	1.504	(4.413)	3.152	(2.529)	−0.310	(0.344)
Import share	0.625	(0.527)	2.780***	(0.798)	0.744	(0.804)	0.846	(0.569)
BEC sectors								
Food and beverages	−1.047***	(0.394)	−13.743***	(3.341)	−1.764*	(1.018)	−3.945**	(1.867)
Industrial supplies n.e.s.	−1.262***	(0.483)	−15.429***	(4.178)	−2.256*	(1.304)	−4.597*	(2.411)
R^2	0.223				0.071			
Pseudo log-likelihood			−628.1				−2,789.6	
Observations	1,000		1,000		1,000		1,000	

Notes: The dependent variable is the *ad valorem* US subsidy payment rate by commodity, s^u_i, for MFP 2018 and MFP 2019, respectively. Observations include food and agricultural commodities (HS chapters 02–24 and 52). Robust standard errors are reported in parentheses. Intercept is excluded from the regression. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% levels, respectively.

Heterogeneity of Impacts by Red-State Share

To investigate whether the electoral geography of US industries was a source of heterogeneity in our estimates on economic factors and sectoral features, we implement our baseline analyses of US Section 301 tariffs and MFP payment rates by allowing for differential impacts from these other factors in relation to the value of the "Red state share" (RSS) variable. To do this, we include interactions for all model covariates with this variable, which yields heterogeneous marginal effects as a function of the value of RSS. This allows us to assess whether, for example, factors such as import share or sectoral features played a more significant role for industries located in Republican-leaning areas of the United States.

For brevity, and because the results obtained by logit are qualitatively similar to those obtained from the linear probability model (LPM), we present only the estimates from the latter estimator. Because the exhaustive set of interactions of red-state share and the BEC indicators would be collinear with the direct of RSS, the excluded interaction is for the "Other goods n.e.s." BEC category in the tariff analysis and "Industrial supplies n.e.s." for the MFP subsidy analysis.

The results for the US tariff analysis accounting for this form of heterogeneity are presented in Table S9. The estimate on RSS can no longer be directly interpreted based only the estimate of its direct effect (with coefficients of 85.493 for the List 1–3 tariffs and 33.077 for the List 1–4a tariffs); consequently, we focus on the estimates of other noteworthy covariates. Notably, the estimates of the interaction effects for each covariate systematically suggest that the impacts of each of these variables are smaller for industries located in more Republican-leaning areas of the United States.

To illustrate with a specific case, the estimated marginal effect of the industry size term X^u is given by $\widehat{\partial t_i^u / \partial X^u} = -0.322 + 0.518 \times \text{RSS}$, implying that industry size has a larger impact in determining the coverage of the US Section 301 tariffs for industries predominantly located in Republican-voting states. Similar results are obtained when accounting for this form of heterogeneity in the MFP subsidy analysis. The estimates on the RSS interactions invariably show that estimates of impacts are attenuated the larger is the value of RSS. To again illustrate the interpretation of these findings with an example, the estimated impacts on the value of net exports from the United States to China are calculated as $\widehat{\partial s_i^u / \partial M} = -21.522 + 44.995 \times \text{RSS}$. Evaluated at the sample mean (RSS = 0.61), we obtain a value of $5.925 = -21.522 + 44.995 \times 0.61$. This estimated effect at the sample average is also quite similar to the estimate on this variable of 5.355 obtained in our baseline specification (see column 1 of Table 5). As in our analysis of US Section 301 tariffs, the findings from this analysis suggest that the determinants of MFP subsidy rates had differential impacts in relation to whether an industry is predominantly located in Republican-voting states.

Table S9. Determinants of US Section 301 Tariffs

	List 1–3 (1)		List 1–4a (2)	
Red-state share (RSS)	85.493**	(42.270)	33.077**	(16.684)
X^u	−0.322**	(0.142)	−0.354***	(0.117)
$X^u \times$ RSS	0.518**	(0.213)	0.439**	(0.171)
Import share	−14.459***	(3.341)	−11.496***	(2.520)
Import share × RSS	24.569***	(5.321)	15.749***	(3.952)
$1/\varepsilon^c$	20.496**	(9.498)	12.927**	(6.379)
$1/\varepsilon^c \times$ RSS	−32.616**	(15.867)	−20.704*	(10.648)
$t_M FN^u$	−9.115***	(1.059)	−2.434***	(0.460)
$t_M FN^u \times$ RSS	15.218***	(1.754)	4.098***	(0.763)
BEC sectors				
Food and beverages	69.494***	(1.828)	43.839***	(0.828)
Food and beverages × RSS	−180.783***	(42.439)	−72.597***	(16.761)
Industrial supplies n.e.s.	25.126***	(1.765)	21.684***	(0.947)
Industrial supplies n.e.s. × RSS	−94.060**	(42.349)	−31.852*	(16.734)
Fuels and lubricants	33.264***	(3.466)	29.289***	(2.721)
Fuels and lubricants × RSS	−98.513**	(42.611)	−38.866**	(17.181)
Capital goods and parts	25.021***	(1.623)	26.414***	(1.064)
Capital goods and parts × RSS	−91.484**	(42.346)	−37.237**	(16.760)
Transport equipment	20.523***	(7.149)	18.173**	(7.101)
Transport equipment × RSS	−82.829*	(43.541)	−23.144	(19.587)
Consumer goods n.e.s.	6.877***	(1.946)	19.177***	(1.146)
Consumer goods n.e.s. × RSS	−79.772*	(42.403)	−35.508**	(16.796)
Other goods n.e.s.	−47.941*	(26.673)	−3.293	(10.515)
R^2	0.789		0.932	
Targeted products	3,746		4,973	
Observations	5,228		5,228	

Notes: The dependent variable is the US ad valorem Section 301 tariff rate on Chinese imports by commodity, t_i^u. Robust standard errors are reported in parentheses. Intercept is excluded from the regression. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% levels, respectively.

Table S10. Determinants of US MFP Subsidies

	MFP 2018		**MFP 2019**	
	(1)		**(2)**	
Red-state share (RSS)	−2.536*	(1.361)	−1.279	(4.008)
t^u	−0.075**	(0.035)	0.084	(0.167)
$t^u \times$ RSS	0.140**	(0.065)	−0.092	(0.271)
t^c	−0.056**	(0.023)	−0.142***	(0.054)
$t^c \times$ RSS	0.090**	(0.037)	0.171*	(0.097)
X^u	0.318	(0.267)	1.944**	(0.852)
$X^u \times$ RSS	−0.260	(0.552)	−2.640*	(1.492)
M	−21.522***	(4.291)	−25.875***	(8.909)
$M \times$ RSS	44.995***	(9.365)	50.465***	(18.234)
Import share	−1.683	(1.888)	−1.527	(3.296)
Import share × RSS	3.840	(4.184)	3.370	(6.946)
BEC sectors				
Food and beverages	1.501*	(0.813)	−6.296	(4.612)
Food and beverages × RSS	−0.085	(0.947)	13.512***	(5.203)
Industrial supplies n.e.s.	1.233*	(0.692)	1.652	(1.914)
R^2	0.252		0.083	
Observations	1,000		1,000	

Notes: The dependent variable is the *ad valorem* US subsidy payment rate by commodity, s_i^u, for MFP 2018 and MFP 2019, respectively. The estimation method is OLS. Observations include food and agricultural commodities (HS chapters 02–24 and 52). Robust standard errors are reported in parentheses. Intercept is excluded from the regression. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% levels, respectively.

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