Trade War and Peace: U.S.-China Trade and Tariff Risk from 2015–2050*

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Abstract

We use the dynamics of U.S. imports across goods in the period around the U.S.-China trade war with a model of exporter dynamics to estimate the dynamic path of the probability of transiting between Normal Trade Relations and a trade war state. We find (i) there was no increase in the likelihood of a trade war before 2018; (ii) the trade war was initially expected to end quickly, but its expected duration grew substantially after 2020; and (iii) the trade war reduced the likelihood that China would face Non-Normal Trade Relations tariffs in the future. Our findings imply that the expected mean future U.S. tariff on China rose more under President Biden than under President Trump. We also show that the trade response to the trade war is similar to the response to the 1980 liberalization that initially granted China access to U.S. markets at NTR terms and was expected to be quickly reversed.

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1 Introduction

The election of Donald Trump to the U.S. Presidency in 2016 brought the issue of trade-policy uncertainty to the forefront. Would he follow through on his campaign pledge to raise tariffs on China and other major trade partners? If so, how long would he leave these tariffs in place? Would he reverse course quickly, as President Nixon did with his import surcharge in 1971?[1] Or, would the tariffs remain in place for decades, as with President Truman's trade embargo on China, which lasted from 1950 to 1971? Once President Trump raised tariffs on China in late 2018, the question of how long these tariffs would last was further complicated by the looming shadow of the 2020 election and the subsequent handover of the Presidency to Joseph Biden.

We answer these questions using disaggregated U.S. import data and a dynamic trade model following the approach developed in Alessandria et al. (2021b). We interpret the differences in import growth across products, and how these differences changed when the trade war began in 2018, through a model with two key features: heterogeneous firms that make forward-looking export participation decisions, and tariff risk that varies across products and time. In the model, Chinese firms make investments in U.S. market access subject to idiosyncratic shocks, industry-specific variation in tariffs across policy regimes, and a common time-varying probability of switching between regimes. We estimate these probabilities by aligning the model's responses to the trade-war tariffs with the responses observed in the data.

We have three main findings. First, despite Trump's campaign rhetoric, there was no increase in the probability that U.S. tariffs on China would rise before the trade war actually began in 2018. The key data moment that identifies this probability is the *trade-war gap elasticity*: the elasticity of U.S. imports from China to the gap between the trade-war tariffs and the Normal Trade Relations (NTR) tariffs. This elasticity was stable in the three years before the Trump tariffs were put in place—imports of products with high trade-war gaps grew at about the same pace as imports of products with low trade-war gaps—which indicates there was no anticipatory response to these tariffs. Second, during the first two years after the trade war began, the probability that tariffs would return to NTR levels was very high—more than 90

[1]On August 15, 1971 Nixon imposed a 10-percent surcharge on all dutiable imports. The surcharge was lifted on December 20, 1971 following the Smithsonian Agreement, which reestablished a set of fixed nominal exchange rates.

percent. However, expectations about the end of the trade war began to shift when President Biden continued the trade war. By 2023, the probability of the trade war ending had fallen to 25 percent. The dynamics of this transition probability are also identified by the behavior of the trade-war gap elasticity, which fell in 2019 after the Trump tariffs were levied, and then stalled before beginning to fall again several years later.

Third, the trade war fundamentally shifted the nature of the uncertainty about U.S. trade policy towards China. Prior to the trade war, since China was granted access to NTR tariffs in 1980, there existed a possibility of reverting to Non-Normal Trade Relations (NNTR) tariffs. This probability did not change with President Trump's election, but it fell when the trade war began.[2] This shift is identified by the behavior of the *NNTR-gap elasticity:* the elasticity of U.S. imports from China to the gap between NNTR and NTR tariffs. Like the trade-war gap elasticity, the NNTR-gap elasticity was stable before the trade war, but began to rise steadily after the trade war began. Because the trade-war gap and NNTR gap are orthogonal, this growth indicates a decline in the likelihood of reverting to NNTR. For perspective, the growth in the NNTR-gap elasticity during the trade-war period is about as large as the growth around China's 2001 accession to the World Trade Organization, which has been cited by Pierce and Schott (2016), Handley and Limão (2017), and many others as evidence that this event reduced policy uncertainty.

Our analysis yields a time-varying forecast of the path of trade and trade policy. We use this forecast to quantify the separate contributions of the Trump and Biden administrations to changes in those paths. We find that, even though Trump raised tariffs and Biden only maintained those tariffs, Trump lowered the discounted expected mean tariff by 2.6 percentage points while Biden raised them by 1.6 percentage points. The lower discounted expected mean tariff under Trump is a result of the reduction in the likelihood of reverting to the NNTR tariff schedule and the high initial probability of a short trade war. The shift in expectations to a long trade war under Biden accounts for the increase in expected future tariffs.

Our analysis also highlights clear parallels between the trade reform in 1980 and the in-

[2]Similarly, Alessandria et al. (2021b) show that the risk of losing NTR access did not materially change with the election of Clinton, George W. Bush, or Obama. However, they argue that Reagan's election in 1981 fundamentally changed the outlook on U.S. trade policy on China, raising the probability of losing NTR access substantially.

crease in tariffs in 2018. The trade responses before and after these two reforms are similar in magnitude. Prior to both reforms, there was no material change in trade that was correlated with the change in tariffs. In the first two years following both reforms, trade changed suddenly by about three times the change in tariffs, and then stalled for two years before beginning to change further. Statistically speaking, we can not reject the hypothesis that the dynamics of the trade elasticity is the same across these two episodes. This suggests that similar expectational dynamics were at work in both cases.

Our paper contributes to a growing literature on the U.S.-China trade war summarized by Fajgelbaum and Khandelwal (2022) and Caliendo and Parro (2023). Beyond their analyses, our novel approach explicitly considers the dynamics of trade substitution and recovers the trade-regime transition probabilities from theory. Our study relates to the trade-policy uncertainty literature, summarized by Handley and Limão (2022), and in particular papers that relate dynamic trade models to the dynamics of trade policy.[3]

In Section 2, we describe our data and present our empirical analyses. In Section 3, we explain our structural model and calibration strategy. In Section 4, we report our quantitative results. Section 5 concludes.

2 Reduced-form empirical analysis

We begin with an empirical analysis of the dynamics of U.S. imports of Chinese goods and their relation to trade policy. We document several novel patterns of import substitution to two measures of good-level trade policy risk.

2.1 Data

The U.S. import data are from the U.S. Census Bureau, aggregated to the 6-digit subheading of the Harmonized System (HS-6), from July 2014 to November 2023. To align trade with the timing of the trade war, we define a year as starting in July and ending in June.[4] We measure trade as the free on board (FOB) value and denote its logarithm v_{igt}, where i indexes

[3]See Ruhl (2011), Alessandria et al. (2017), Handley and Limão (2017), Steinberg (2019), Alessandria et al. (2019), Alessandria et al. (2021b), and Hoang and Mix (2023).

[4]Applied tariffs begin rising in July 2018, so we define a year as beginning in July. For example, our year 2019 begins in July 2018 and ends in June 2019. In the online appendix, we show that our empirical results are robust to using the standard January–December definition.

the source country and g indexes the HS-6 *good*. The applied tariff, τ_{igt}, is the applied duty levied on g divided by its FOB import value. We focus on a balanced sample—goods imported from China every year—and exclude goods that were affected by trade policies that were not China-specific, e.g., the Section 232 steel and aluminum tariffs from 2017 and the temporary tariffs imposed on Mexico in 2019.

The trade-war increases in tariffs on Chinese goods were large and widespread. Figure 1(a) plots the paths of the 25th, 50th, and 75th percentiles of the tariff distribution. The median tariff rises from about 3 percent in January, 2018 to 10 percent by October, 2018. By August, 2019, the median tariff is about 25 percent. The lower and upper quartiles increased by similar amounts. In Figure 1(b), we plot the distribution of tariffs in 2017 and 2022. Relative to 2017, the trade-war tariff distribution has shifted significantly to the right and its variance has increased.

We construct two measures of a firm's good-specific tariff risk. Each measures the additional tariff rate a good faces in the bad regime. We define a good's NTR tariff rate as the average applied tariff on Chinese exports to the United States in 2015–2017. The *trade-war gap* is the difference between the average applied tariff to China in 2020–2023 and the NTR tariff rate. The *NNTR gap* is the difference between the NNTR tariff rate and the NTR tariff rate,

$$X_g^j = \log(1 + \tau_g^j - \tau_{g,15-17}^{NTR}), \quad j = \{NNTR, TW\}. \tag{1}$$

The NNTR rates were set by the Smoot-Hawley Tariff Act in 1930 and remain unchanged.

In Figure 2(a), we plot the distribution of the trade-war gap and the NNTR gap. The NNTR-gap distribution has a fatter tail than the trade-war gap distribution. Moving from NNTR to NTR rates was a significant liberalization for Chinese firms. The trade-war gap distribution is bimodal, with a peak near zero and a peak at 25 percent. Figure 2(b) is evidence of an important feature of the data: the trade-war gaps and the NNTR gaps are orthogonal. The correlation between the two is –0.08.

2.2 Elasticities of trade to the trade-war gap and the NNTR gap

We extend the approach of Pierce and Schott (2016) by measuring the dynamics of trade with respect to the two tariff risks. We estimate the trade-war gap elasticity and the NNTR-gap elasticity from 2015 to 2024,

$$\log v_{igt} = \sum_{t=2015}^{2024} \left(\beta_t^{NTR} X_g^{NTR} + \beta_t^{TW} X_g^{TW}\right) \mathbb{1}_{\{i=China \,\wedge\, t=t'\}} \qquad (2)$$
$$+ \delta_{gt} + \delta_{ig} + \delta_{iht} + \log c_{igt} + u_{igt},$$

where δ_{ig} and δ_{gt} are country-good, and good-time fixed effects; δ_{iht} is a country-time fixed effect at the HS-Section level, and c_{igt} is a measure of shipping costs.[5] We focus on annual data to avoid concerns about stockpiling in advance of possible tariff changes.[6] As is common in event-studies, we reference the source-good fixed effects to the year before the tariffs rise, 2018. The coefficient β_t^{TW} measures the elasticity of U.S. imports from China to the trade-war gap, relative to all other countries, at time t, relative to 2018. Similarly, β_t^{NTR} is the NNTR-gap elasticity relative to the same benchmarks. The fixed effects control for good-level U.S. demand shocks, time-invariant bilateral trade barriers, and aggregate shocks to exporting countries.

Figure 3(a) plots the estimates of equation (2). The trade-war gap elasticity was statistically indistinguishable from zero during 2015–2017, indicating that there was no change in the likelihood of a trade war during this period. During 2019–2020, the trade-war elasticity falls to about –2.8, reflecting the fall in imports in response to higher tariffs that one would expect to see. From 2021 onward, the trade-war gap elasticity falls gradually by another 1.3 points. There are two possible explanations for the growing substitution: trade was gradually adjusting to the increase in tariffs or the likelihood that these tariffs would be reversed was falling. This is because the trade-war gap has a dual meaning: it represents the size of the past tariff increase imposed in the trade war, but also the size of the potential future tariff reduction if the trade war ends. A structural model is needed to determine the quantitative importance of these two channels.

The NNTR-gap elasticity, the traditional measure of good-level trade policy risk, was also statistically indistinguishable from zero during 2015–2017, indicating that the probability of

[5] We measure shipping *charges* as the difference between the CIF import value and the FOB import value. c_{igt} is the logarithm of one plus a good's charges divided by its FOB import value.

[6] Alessandria et al. (2019) show stockpiling was common in the 1990s in the period around the annual NTR renewal decision in July. Khan and Khederlarian (2021) show anticipatory destocking was common and large in advance of scheduled NAFTA tariff cuts. In the online appendix, we report estimates at the quarterly frequency.

going back to NNTR status was stable during this period. In 2019, this elasticity began to rise, culminating in an increase of almost one log point by 2024. This is notable because the NNTR gap is orthogonal to the trade-war gap (Figure 2(b)). The trade war did not, on average, increase tariffs on goods with high NNTR gaps relative to goods with low NNTR gaps. Nevertheless, U.S. imports of Chinese goods with high NNTR gaps grew relative to imports of low-gap goods, which indicates that the trade war reduced the likelihood of going back to NNTR status. Our interpretation of this result is that the trade war fundamentally changed the nature of U.S.-China trade-policy uncertainty. Prior to the trade war, the uncertainty was about moving between the NNTR and NTR policy regimes. After the trade war began, the uncertainty was about moving between trade war and "trade peace."

In the online appendix, we show that our results are robust to varying the level of aggregation (good and time), an unbalanced sample, and a host of additional controls. Most importantly, our results are robust to a specification that includes European Union imports, in which we can include exporter-good-time fixed effects to control for good-level supply conditions.

3 The structural model

We interpret our empirical findings using a structural model that enables us to quantify the evolution of expectations regarding U.S. trade policy towards China. Additionally, we aim to distinguish the effects of these changes in expectations on trade from the gradual adjustments to the trade-war tariffs.

3.1 Environment

There are G goods that correspond to the 6-digit HS goods in our empirical analysis. Within each good g, there is a fixed mass of Chinese firms that produce differentiated varieties and face idiosyncratic shocks to productivity, trade costs, and survival. Accessing the U.S. market requires firms to pay a fixed cost that depends on its current export participation status. There are three trade policy regimes: normal trade relations, or *trade peace* (P), non-normal trade relations (N), and the trade war (W). The probability of switching between regimes varies over time, creating time-varying trade-policy uncertainty.

Trade policy. The good-level tariff, $\tau_g(s)$, depends on the current tariff regime, $s \in \{\text{P, N, W}\}$.

The tariff regime follows a time-varying Markov process with transition probabilities $\omega_t(s, s')$. Before the trade war, the economy is in the trade-peace regime, the probabilities of transitioning to the NNTR regime (and back) are constant, and the probability of a trade war is zero.[7] The transition probabilities are

$$\Omega^P = \begin{bmatrix} \rho^P & 1-\rho^P & 0 \\ 1-\rho^N & \rho^N & 0 \\ 1-\rho^W_{18} & 0 & \rho^W_{18} \end{bmatrix}. \tag{3}$$

Note that ρ^W_{18} is not identified, but is also irrelevant because switching to the trade-war regime is a zero-probability event.

When the trade war begins, the economy switches to the trade-war regime. We assume that this change is unexpected, which is consistent with a constant and zero trade-war gap elasticity prior to 2019. The probability of transitioning from the trade-war regime back to the trade-peace regime is time-varying and the key parameter of interest. The probability of transitioning from the trade-peace regime to the trade-war regime is constant and equal to the probability of exiting the trade-peace regime before the trade war. It is no longer possible to transition to the NNTR regime from either the trade-war or trade-peace regime.[8] The trade-war transition matrix in period t is

$$\Omega^W_t = \begin{bmatrix} \rho^P & 0 & 1-\rho^P \\ 1-\rho^N & \rho^N & 0 \\ 1-\rho^W_t & 0 & \rho^W_t \end{bmatrix}. \tag{4}$$

[7]This assumption is consistent with the history of U.S. trade policy until the trade war. Since the end of World War II, most country-level changes in U.S. trade policy have involved moving between NTR to NNTR tariffs. In 1951, the Soviet Union and most other communist countries were moved from NTR to NNTR. Other examples of transitions from NTR to NNTR include Poland (1982), Romania (1989), Bulgaria (1989), Hungary (1989), Russia (2022), and Belarus (2022). For non-market economies, transitions from NNTR to NTR status happen at different points. For example, China and Vietnam gained NTR status in 1980 and 2001, respectively.

[8]This is a normalization that is mostly without loss of generality. We can only identify the change in the probability of transitioning to NNTR after the trade war began (not separate levels of this probability before and after the trade war) because our empirical estimate of the NNTR-gap elasticity is normalized to zero in 2018. Alternatively, we could (i) assign a constant, positive post-2018 probability of switching to NNTR and identify ρ^P in the same way, or (ii) assign a constant, positive value to ρ^P and identify the post-2018 probability of switching to NNTR. Either way, our approach would recover a similar change in the probability of switching to NNTR between the pre- and post-2018 periods.

We assume that the changes in Ω_t^W from one year to the next are unanticipated; firms do not know the entire path of $\{\Omega_t^W\}_{t=2019}^{\infty}$ in advance. This is consistent with the assumption that the onset of the trade war itself is unanticipated, and it allows us to estimate changes in Ω_t^W during our observation period using the dynamics of the trade-war gap elasticity without taking a stand on how Ω_t^W might evolve in the future. We study an alternative model in which firms have perfect foresight over $\{\Omega_t^W\}_{t=2019}^{\infty}$ in Section 4.3.

Trade costs. Firms pay variable costs of exporting (ξ) and fixed costs of entering the U.S. market (f_{g0}) and continuing in the market (f_{g1}). The variable cost takes three values ($\infty > \xi_{gH} > \xi_{gL}$) and follows a stationary first-order Markov process. When $\xi = \infty$, the firm is a nonexporter. When a firm enters the export market, $\xi = \xi_{gH}$, and switches to $\xi = \xi_{gL}$ with probability $\rho_\xi \in (0, 1)$. This specification implies exporters start with high variable costs and, with repeated investments and some luck, gain access to the low-cost technology and expand their exports. The fixed costs are a function of the firm's export participation status. We summarize the fixed-cost structure as a function $f_g(\xi)$, where $f(\infty) = f_{g0}$ and $f(\xi_{gL}) = f(\xi_{gH}) = f_{g1}$. This setup generalizes the sunk-cost model of Das et al. (2007) in a way that can capture the exporter life cycle documented by Ruhl and Willis (2017).

Production and demand. Firms produce using labor, $y = z\ell$. Productivity, z, is independent across firms and follows a stationary Markov process. U.S. demand for a firm's good, d_{gt}, is a downward-sloping function of the tariff and the price the firm charges, p,

$$d_{gt}(p, s) = (p\tau_g(s))^{-\theta_g} D_{gt}, \tag{5}$$

where D_{gt} is an aggregate demand shifter and θ_g is the price elasticity of demand.

3.2 Optimization

The firm's export status is determined in the prior period. The firm maximizes current-period profits by choosing its price, taking as given its residual demand and the wage, w,

$$\pi_{gt}(z,\xi,s) = \max_{p,\,\ell} p\, d_{gt}(p,\tau_g(s)) - w\ell \tag{6}$$

$$\text{s.t. } \; z\ell \geq d_{gt}(p,\tau_g(s))\xi. \tag{7}$$

The value of a firm that chooses to export at $t+1$ is

$$V^1_{gt}\left(z,\xi,s\right) = -f_g(\xi) + \frac{\delta(z)}{1+r}\sum_{s'}\omega_t(s,s')\,\mathop{\mathbb{E}_{\mathrm{t}}}_{z',\xi'} V_{g,t+1}\left(z',\xi',s'\right), \tag{8}$$

where r is the interest rate used to discount future profits. The value of a firm that chooses not to export at $t+1$ is

$$V^0_{gt}\left(z,\xi,s\right) = \frac{\delta(z)}{1+r}\sum_{s'}\omega_t(s,s')\,\mathop{\mathbb{E}_{\mathrm{t}}}_{z'} V_{t+1}\left(z',\infty,s'\right). \tag{9}$$

Given these objects, the value of the firm is

$$V_{gt}\left(z,\xi,s\right) = \pi_{gt}(z,\xi,s) + \max\left\{V^1_{gt}\left(z,\xi,s\right), V^0_{gt}\left(z,\xi,s\right)\right\}. \tag{10}$$

The break-even exporter, who is indifferent between exporting and not exporting, has productivity $\bar{z}_{gt}(\xi)$ such that

$$V^1_{gt}\left(\bar{z}_{gt}(\xi,s),\xi,s\right) = V^0_{gt}\left(\bar{z}_{gt}(\xi,s),\xi,s\right). \tag{11}$$

This equation can be rewritten as

$$f_g(\xi) = \frac{\delta(z)}{1+r}\sum_{s'}\omega_t(s,s')\left\{\mathop{\mathbb{E}_{\mathrm{t}}}_{z',\xi'}\left[V_{t+1}(z',\xi',s')\right] - \mathop{\mathbb{E}_{\mathrm{t}}}_{z'}\left[V_{t+1}(z',\infty,s')\right]\right\}, \tag{12}$$

which says that, for the marginal firm, the fixed cost of exporting equals the expected present value of the gain in firm value from exporting in the future. Crucially, this latter object depends on the entire expected path of future tariffs, not the current applied tariff rate.

3.3 Calibration

We calibrate our model in four stages. First, we map the model to the data by grouping goods into 15 broad sectors. Second, we assign standard values from the literature to several parameters. Third, we calibrate the parameters that govern exporter dynamics to match moments from Chinese firm-level data before the trade war. Fourth, we calibrate the probabilities of switching between trade-policy regimes to match our estimated dynamics of the elasticities of imports to the trade-war gap and the NNTR gap from Section 2. Table 1 provides an overview of our calibration.

Mapping goods to sectors. We assign each 6-digit HS good to one of 15 2-digit sectors in the China Industrial Classification System. We denote this assignment by a function $\gamma(g)$. We assume that the demand elasticity, θ_g, productivity dispersion, σ_{gz}, and the export costs, f_{g0}, f_{g1}, ξ_{gH}, and ξ_{gL}, vary across sectors but are the same for all goods within a sector, e.g., $\theta_g = \theta_{\gamma(g)}$ and $\sigma_{gz} = \sigma_{\gamma(g)z}$.

Functional forms and assigned parameters. The model period is one year. We normalize the wage to one and set the interest rate to four percent. The productivity process is

$$\log a' = \rho_z \ln a + \varepsilon, \qquad \varepsilon \overset{iid}{\sim} N(0, \sigma^2_{\gamma(g)z}), \tag{13}$$

where $z = \frac{1}{\theta-1}\log a$. The persistence parameter, ρ_z, is common to all firms, while the variance of the innovations, $\sigma^2_{\gamma(g)z}$, differs across sectors. The probability of firm survival is $\delta\left(a\right) = 1 - \max\left[0, \min\left(e^{-\delta_0 a} + \delta_1, 1\right)\right]$, which implies that higher-productivity firms are more likely to survive. We take the values of ρ_z, δ_0, and δ_1 from Alessandria et al. (2021a). The import demand elasticities, $\theta_{\gamma(g)}$, are from Soderbery (2018). The low idiosyncratic iceberg trade cost, $\xi_{\gamma(g)L}$, is normalized to one for all sectors without loss of generality. The persistence of this cost, ρ_ξ, is taken from Alessandria et al. (2021b). Finally, we also take the probability of switching from the NNTR regime to the trade-peace regime, $1-\rho^N$, from Alessandria et al. (2021b), as this parameter can only be identified by data from before 1980, when China first gained NTR status. Their estimate is that $\rho^N = 0.71$.

Parameters determined before the trade war. The parameters that govern production and exporter dynamics, $\sigma_{\gamma(g)z}, f_{\gamma(g)0}, f_{\gamma(g)1}$, and $\xi_{\gamma(g)H}$, are chosen to match moments from Chinese firm-level data under the assumption that in 2018, the economy has been in the trade-peace regime for many years, but the probability of switching to NNTR is non-zero.[9] The moments are: the dispersion in log export sales; the fraction of firms that export; the fraction of exporters that stop exporting next period; and the ratio of the average exports of incumbent exporters to new exporters. These moments are computed separately for each sector in both the model and the data; the partial-equilibrium nature of our model allows us to perform this part of the calibration procedure one sector at a time. The empirical moments are taken from Alessandria et al. (2021b) and are reported in Table 2 while our estimated parameters are reported in Table 3.

Parameters determined during the trade war. We calibrate the probabilities of switching trade-policy regimes to match our estimates of the dynamics of the elasticities of trade to the trade-war gap and the NNTR-gap. The probability of switching from trade peace to NNTR before 2019, $1-\rho^{P}$, is identified by the change in the NNTR-gap elasticity between 2018 and 2024. The higher this probability, the more imports of goods with high NNTR gaps will grow relative to imports of goods with low NNTR gaps once the trade war begins and going back to NNTR is no longer possible.

The probability of switching from trade war to trade peace, $1-\rho^{W}_{t}$, is identified by the dynamics of the trade-war gap elasticity in the subsequent periods. For example, ρ^{T}_{2019} is identified by the trade-war gap elasticities in 2020 onward and ρ^{W}_{2020} by the elasticities in 2021 onward. Given that our elasticity estimates end in 2024, we assume that the probability of ending the trade war is constant from 2024 onward: $\rho^{W}_{t}=\rho^{W}_{2023}$. We explore the sensitivity of our results to this assumption.

4 Results

First, we discuss our model's ability to account for the trade dynamics following the onset of the trade war and our estimates of trade-policy expectations that are implied by these dynamics. Second, we study the implications of our estimates for the future of U.S.-China trade. Third,

[9]Recall that, in this period, the probability of the trade war starting is zero.

we study the role of trade-policy uncertainty in explaining the observed trade dynamics using a counterfactual model in which the trade war is always expected to be permanent. Finally, we relate the current substitution patterns and risks to the trade liberalization in 1980.

4.1 Dynamics of trade flows and trade policy

Figure 3(a) shows the elasticities of Chinese imports to the trade-war gap and the NNTR gap in the model and data. The model successfully captures the dynamics of both elasticities. The trade-war gap elasticity falls sharply between 2018–2020, and then continues to fall gradually over the following four years. The NNTR-gap elasticity begins to rise after 2018, although, initially, it rises more slowly in the model than in the data. The model reproduces the cumulative change in this elasticity over the observation period.

Figure 4(a) plots our main finding: the implied probabilities of switching between trade-policy regimes. Before the trade war began in 2019, the probability of moving from trade peace to NNTR was 11.8 percent. Once the trade war began, the probability of moving back to trade peace was initially high at 70.0 percent in 2019 and 57.0 percent in 2020, but then fell sharply, reaching 16.7 percent in 2024.

We use our model to quantify the change in the path of trade policy in each President's administration. In Table 4, we report two measures for each President: 1) the expected duration of the trade war and 2) the change in the mean discounted tariff. The expected duration is just the inverse of the transition probability in the final full year of each President. The mean discounted expected tariff uses the discount factor, $\beta = 1/(1+r)$, to weight expected future tariffs, and is equal to

$$\tau_t^E = \frac{1}{G}\sum_{g=1}^{G}(1-\beta)\left(\sum_{s=t}^{\infty}\beta^{s-t}\mathbb{E}_t[\tau_{gs}]\right). \tag{14}$$

While Trump raised the average applied tariff by 17 percentage points, the mean discounted tariff fell by XX percentage points (Table 4, "baseline"). The mean discounted tariff falls because the trade-war regime has a lower average tariff than the NNTR regime and the trade war is very likely to end in 2019–2020. At the end of the Trump presidency, the expected duration of the trade war is 1.8 years. Under Biden, the average applied tariff does not change, but the mean discounted tariff increases by 1.1 percentage points. This is driven by the falling probability of ending the trade war in 2021–2024. The expected duration of the trade war in 2024 is 6 years.

4.2 Implications for the future of U.S.-China trade policy and trade

Our estimated model yields forecasts of the evolution of U.S.-China trade policy and trade flows. We now discuss these forecasts. We also consider some extreme paths of trade policy to illustrate the mechanics of the model and the role of expectations.

Figure 5(b) plots the probability of being in the trade-peace regime, conditional on being in the trade-war regime in 2024. For reference, we include the unconditional probability that China is in the trade-war regime since 1949 (40 years out of 74, or about 54 percent). The conditional probability of being in the trade-peace regime in 2025 is $1 - \rho^T_{2024} = 0.17$, but this probability rises over time and eventually surpasses the unconditional probability in 2031. In the long-run, China is expected to be in the trade-peace regime with probability 58.6 percent.

Figure 4(c) plots the evolution of the expected mean tariff. The "mean simulation" line is the average trade-peace tariff until 2019, the average trade-war tariff from 2019-2024, and the average expected tariff from 2024 onward. The "2020 beliefs" line is the expected path of tariffs from 2020 onward, conditional on being in the trade war state in 2020. The expected tariff falls sharply, reflecting the high probability of trade peace in 2021 in Figure 4(a). The 2020-beliefs tariff and the mean-simulation tariff converge to the same long-run value because the transition probabilities are the same in the two cases. The "2015 beliefs" line is the expected mean tariff conditional on being in the trade-peace regime in 2015. This expectation uses the pre-war transition probabilities. The long-run expected average tariff is about two percentage points higher than the post-war long-run average because the NNTR regime has higher average tariffs than the trade-war regime.

What do our estimates imply about the future dynamics of U.S. imports from China? In Figure 4(d), we plot aggregate trade under different scenarios. In the "uncertain trade war" scenario, the economy is in a realization of uncertainty in which the trade war continues indefinitely, even though the probability the trade war ends is $1 - \rho^W_{2023} = 0.17$. In this scenario, trade would continue to decline, as Chinese exporters gradually adjust to the trade-war tariffs and the decreasing probability of trade peace during 2019–2023. In the long run, the aggregate level of U.S. imports from China would be almost 60 percent lower than before the trade war.

The "uncertain trade peace" scenario considers a realization of uncertainty in which the trade war ends in 2025, and never restarts, even though the trade war could restart with probability $1 - \rho^P = XX$. In this scenario, aggregate trade would completely recover even though there is a chance the trade war could restart, because there is no longer a chance of ending in in the NNTR regime.

Our last approach is to consider the distribution of possible future outcomes by simulating a large number of potential trade-policy sequences, $\{s_t\}_{t=2025}^{\infty}$, using the transition matrix Ω_{2023}^W. In some of these sequences, the trade war ends after a few years, in others it ends after many years, and in still others it starts and stops many times. In Figure 4(d), we plot the mean path of U.S. imports from China in these simulations. Average trade grows from its 2024 level, but the long-run aggregate decline in trade is about 20 percent from its 2018 level.

4.3 Alternate expectations

In this section, we explore how our assumptions about the dynamics of trade policy expectations influence our results.

Perfect foresight over transition probabilities. First, we consider a model with alternative expectations about future transition probabilities. Rather than treating the year-to-year changes in the transition matrix Ω_t^W are unanticipated, here we assume that firms have perfect foresight over the entire path $\{\Omega_t^W\}_{t=2019}^{\infty}$ once the trade war begins. Figure 4(a) shows that this "perfect foresight" model yields qualitatively similar transition probabilities to our baseline model, but the likelihood of the trade war ending is consistently higher, especially in 2019 and 2020. At the end of the Trump presidency, the expected duration of the trade war is about one year and, in 2024, under Biden, it stands at 4.7 years (Table 4, "perfect foresight"). The different transition probabilities lead to XX differences in the innovations to the expected tariffs of each administration. In the perfect-foresight model, compared with the baseline model, the discounted tariff fell XX during the Trump administration and rose XX during the Biden administration.

Eliminating policy uncertainty. Second, we evaluate the effects of policy reforms that eliminate all uncertainty about future trade policy. In the "permanent trade war" scenario, we assume firms initially operate under the original pre-trade war transition matrix, Ω^P, but, when the trade war starts, they believe it will be permanent. As seen in Figure 4(d), on impact, trade falls by the same amount as in our baseline trade-war scenario, but then continues to fall further. In the long run, aggregate trade stabilizes at -0.85 log points below the pre-trade war level—a 60 percent larger drop than in the baseline case—despite the tariff paths being identical.

At the other extreme, in the "permanent trade peace" scenario, we assume the economy follows the baseline case until 2025, at which point the trade war ends and is expected to never resume. We assume that going back to the NNTR regime is no longer possible, either; this scenario is a deeper form of integration than the pre-trade war status quo. On impact, imports increase by the same amount as in the uncertain trade-peace scenario (Section 4.2), but grow more in subsequent periods, ultimately converging to 25 percent above the pre-trade war level. The gap in imports between the permanent and uncertain versions of trade peace arises from the increase in export participation caused by the elimination of uncertainty, including the possibility of restarting the trade war as well as the possibility of moving to the NNTR regime.

Across-the-board tariff increases. Third, we study the effects of anticipation about the possibility of across-the-board (ATB) tariff increases that apply to all goods, instead of or in addition to the trade-war tariffs that were actually levied. We allow for two such changes: a pre-war ATB tariff increase of 10% above trade-peace levels that can occur starting in 2017; and a post-war ATB increase of 10%above trade-war levels that can occur starting in 2022.[10] In each case, we reduce the persistence of the prevailing state (peace in the first case and war in the second) by half and assign the remaining probability weight to the ATB tariff hike. Figure 5 shows that allowing for these additional events has essentially no effect on the dynamics of the elasticity of trade to either the NTR and trade-war gaps, and therefore no effect on our estimates of the likelihood of the trade war ending. This is because these ATB tariff increases are orthogonal to the both NNTR tariff schedule and the actual trade-war tariff distribution.

If anticipation of ATB tariff increases doesn't affect the gap-elasticity dynamics, where should one look for evidence of this anticipation? The obvious answer is aggregate trade: ATB

[10] We have also explored the effects of a lower bound on tariffs that only affects goods with low tariffs. The results are almost identical.

tariff increases affect all goods equally, so anticipation of these increases should have similar effects on trade dynamics across goods. However, aggregate U.S. imports from China in recent years have been affected by several major events in addition to the trade war, most notably the COVID-19 pandemic. To control for these effects, we look at the country-HS section-year fixed effects from (2). We find that there are no statistically distinguishable year-to-year changes; in fact, none of the point estimates themselves are statistically significant at all. This suggests that there were no meaningful changes in the likelihood of ATB tariff increases during our observation period, either before or after the trade war began.

4.4 Parallels to U.S.-China integration

The trade war was a large change in U.S. tariffs on China. Another large change occurred in 1980, when the United States granted China "conditional" normal trade relations, lowering tariffs on Chinese goods dramatically, subject to annual renewal by the U.S. President. In this section, we show that trade is adjusting to the current reform in a way similar to the earlier reform, albeit in the opposite direction, and we discuss the role of policy credibility in the two episodes.

In Alessandria et al. (2021b), we use a version of equation (2) to estimate annual NNTR-gap elasticities during 1974–2008. In Figure 3(b), we plot these estimated NNTR-gap elasticities against the trade-war gap elasticities from Figure 3(a), each normalized to zero in the year before the relevant reform (1979 for the NNTR-gap elasticities and 2018 for the trade-war gap elasticities). The trade elasticities in the two episodes are remarkably similar. In 2024, five years into the trade war, the elasticity of U.S. imports from China to the trade-war gap was about four. In 1985, five years after China was granted conditional NTR status, the NNTR-gap elasticity was also about four. Looking ahead, growth in the NNTR-gap elasticity accelerated in the mid-1980s and the trade elasticity more than doubled in the next five years. The NNTR-gap elasticity would rise to almost 11 in 2001, when China joins the WTO.

Alessandria et al. (2021b) find the slow adjustment of U.S. imports from China following the 1980 liberalization can be attributed to the lack of initial credibility of that policy change. As U.S.-China relations improved throughout the 1980s, the policy gained credibility and the probability of losing the low-tariff regime fell. The low initial credibility discouraged Chinese firms to invest in U.S. market access but, as the reform gained credibility Chinese firms invested in market access and trade grew rapidly. A similar adjustment appears to be at work during the trade war. The new tariffs were initially perceived as temporary, but as time passed, the trade-war regime gained credibility and U.S. imports have increasingly substituted away from Chinese sources. If history repeats itself, and expectations of remaining in the trade-war state rise, we should expect to see further substitution away from Chinese goods.

The trade liberalization in 1980 can help us understand the trade war. The perceived credibility of both reforms was initially low, and for the earlier reform, grew as time passed. In both episodes, we find policy credibility to be intertwined with the political cycle in the United States and important geopolitical considerations in similar ways.[11]

The 1980 reform was preceded by the normalization of relations with China by President Carter. It involved the removal of diplomatic relations with Taiwan and the end of the Mutual Defense Treaty. It was a large shift in foreign policy that did not involve Congress. Congress quickly and overwhelmingly passed the Taiwan Relations Act in 1979, which required military support of Taiwan. It was a shift in foreign policy that treated China and the USSR equally on trade and created significant uncertainty over the state of U.S.-China policy. It was an important point of contention in the subsequent Carter-Reagan election. Reagan campaigned on restoring relations to Taiwan and in the early stages of his presidency took steps in this direction. Only with President Reagan's visit to China in 1984 did the relationship begin to take hold and become more credible.

Similarly, the 2018 reform was a substantial shift in trade policy on imports from China. Nearly every U.S. presidential election, going back to Carter-Reagan in 1980, featured discussion of trade restrictions on China, but ended with only minor changes in trade policy. In the 2020 election between Trump and Biden, Trump supported his tariffs while Biden pushed to engage China on a multilateral basis. However, since Biden came to office in 2021, there has been no substantial change in trade policy. Industrial policy in the Biden Administration, in both the Chips and Science Act and Inflation Reduction Act in 2022, further restricted imports from China in certain industries.

[11] The online appendix includes a timeline of several key moments in U.S.-China relations.

5 Conclusion

The conventional view, that China's membership in the WTO precluded a future high-tariff regime, has been proven false. Our findings offer a new narrative on U.S.-China trade relations that helps us understand the post-2018 data. A trade war was always possible, but the risk did not increase in advance of the trade war. Despite raising tariffs, and resetting trade policy risks, we find the expected path of tariffs when Trump left office was lower than when he started. Under Biden, this path has shifted up as the trade war is expected to last four more years or longer.

Our estimates of the trade-policy process rely on heterogeneity in tariff risk from the U.S. tariff system, the observed tariffs from the trade war, trade dynamics, and a forward-looking model of exporting. It is based on the decisions of the firms most affected by trade policy and leverages unique aspects of the heterogeneity in trade policy. Alternative tariff risk processes could yield different model outcomes, but should be disciplined by the dynamics of trade flows to old and new tariff risks. Likewise, alternative forward-looking models, could be used to discipline the process for tariffs. Static models of the type used in most analyses of the trade war (e.g., Fajgelbaum et al., 2020) are unusable to extract expectations of trade policy and are inconsistent with the dynamics of trade flows since the onset of the trade war. Existing work on the aggregate effects of changes in trade policy in static and dynamic models (Alessandria et al., 2021a; Mix, 2023) suggests a need to revisit both the aggregate effects and welfare estimates. Our estimates of the stochastic path of trade policy could be an input to such an analysis.

Aspects of the dynamics of disintegration of U.S.-China trade and trade relations look quite similar to the integration following the normalization of relations in 1980, but in reverse. Owing to geopolitical considerations and political turnover in each country, that prior reform took time to be viewed as credible, which depressed import growth. Similar dynamics are at play on the eve of the 2024 U.S. Presidential election.

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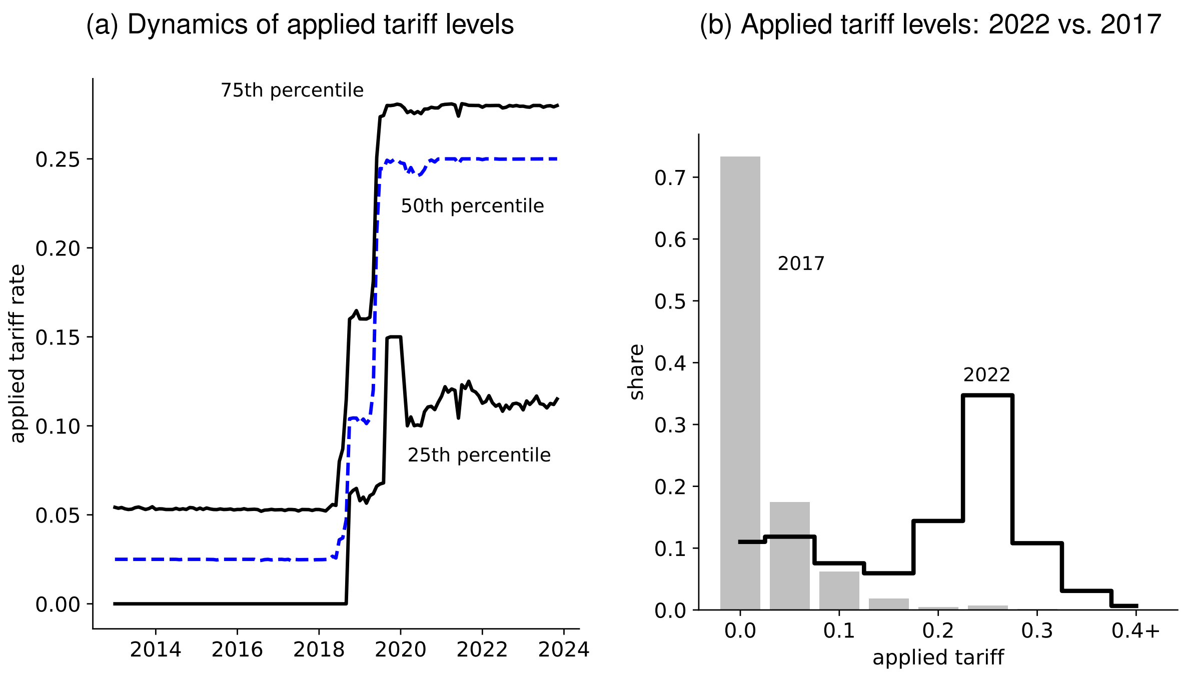
Figure 1: U.S. tariffs on Chinese imports

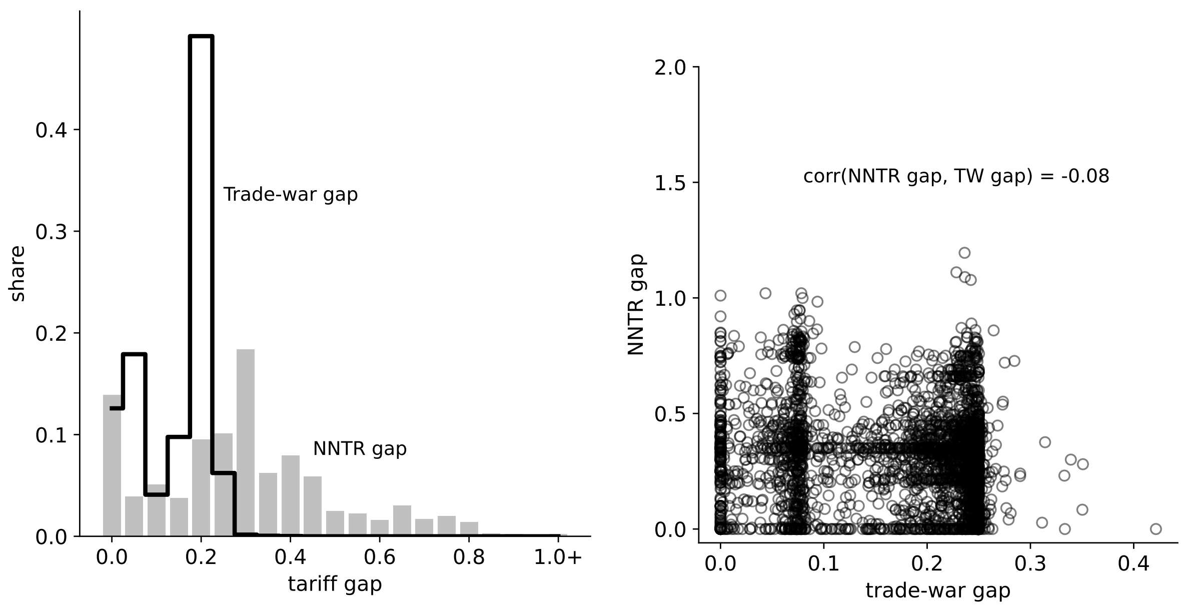


Notes: The applied tariff is, for each HS 6-digit subheading, duties collected divided by the f.o.b. trade value of trade. Panel (a) plots each year's 25th, 50th, and 75th percentile applied tariff. Panel (b) plots the applied tariff distribution in 2017 and 2022. A year begins in July of the previous year and ends in June of that year, e.g., 2024 is July, 2023 to June 2024.

Figure 2: The NNTR and trade-war tariff gaps

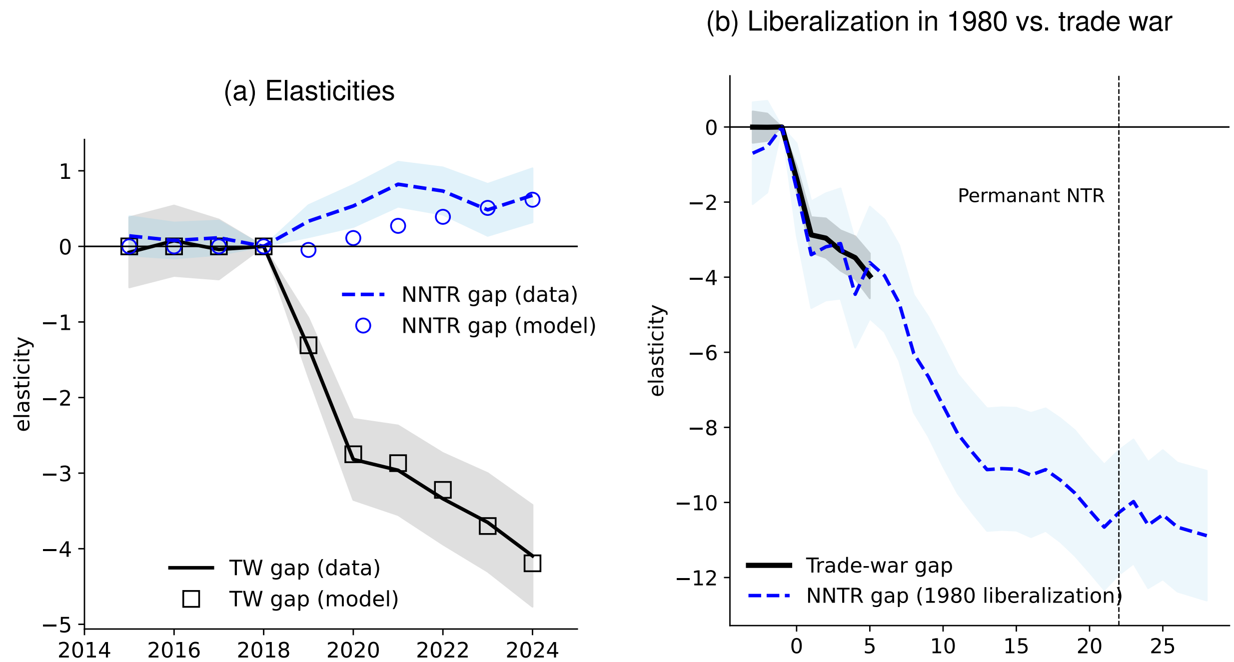
(a) Tariff-gap distributions

(b) Tariff-gap correlation



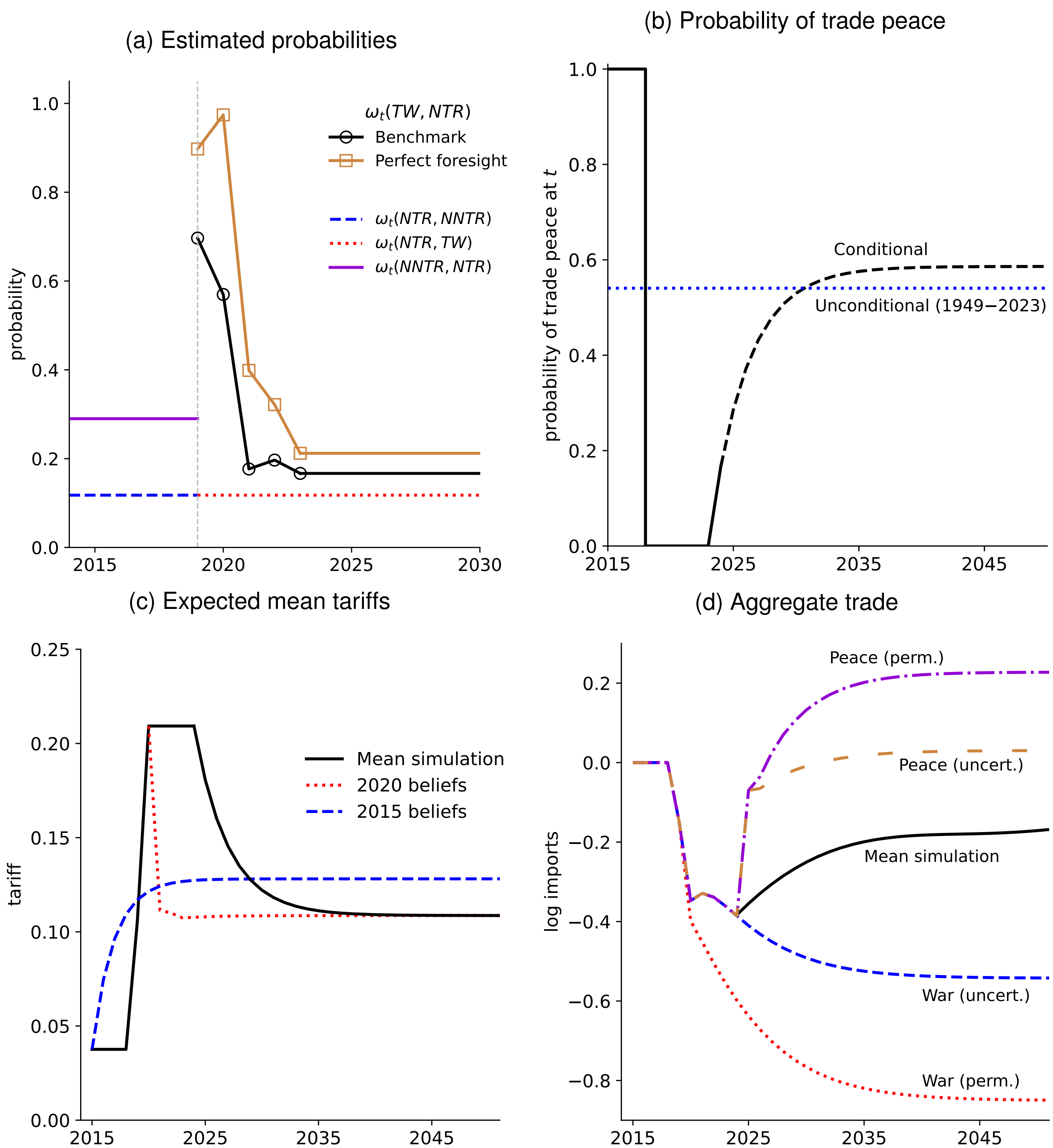
Notes: The *trade-war gap* is the applied tariff rate averaged over 2020–2023 minus the NTR tariff rate, where the NTR tariff rate is the applied tariff rate averaged over 2013–2017. The *NNTR gap* is the NNTR tariff rate minus the NTR tariff rate. Panel (a) plots the empirical distribution of each tariff gap. Panel (b) plots the trade-war gap against the NNTR gap.

Figure 3: Elasticity of imports from China to the NNTR and trade-war gaps



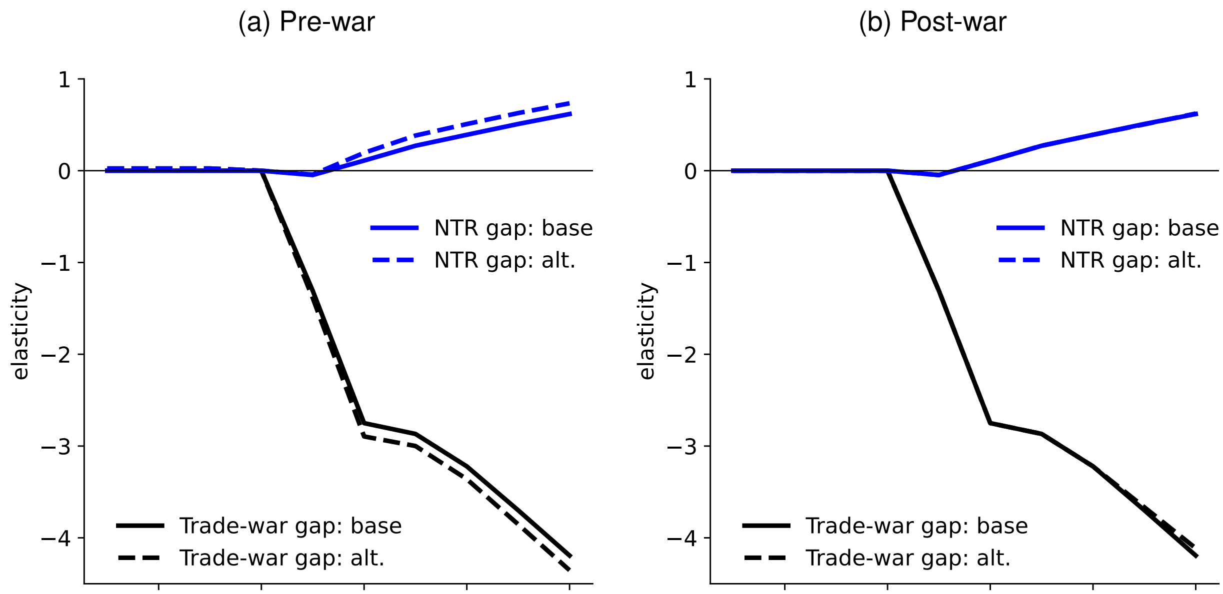
Notes: Panel (a) plots the coefficients β_t^{NNTR} and β_t^{TW} from (2). The coefficients are the elasticities of U.S. imports from China, relative to other countries, with respect to the tariff gap. Panel (b) plots the trade-war elasticities from panel (a) and the elasticities from 1976–2008 that coincide with the granting of conditional NTR. The vertical line “Permanent NTR” denotes 2002, when China joins the WTO.

Figure 4: Model projections



Notes: Panel (a) plots the transition probabilities estimated under our baseline expectations and with surprises. Panel (b) plots the state of the economy between peace and war through 2024 and forecasts from 2025 onwards using the baseline transition matrix. The line Unconditional is the share of years in the Peace between 1949-2023. Panel (c) plots the expected path of tariffs based on expectations in 2015 and 2020. Mean simulation is the observed mean tariff through 2024 and the expected path beyond based on the transition probability estimated in the baseline case. Panel (d) plots the path of tariffs under different scenarios. Peace and War denote continuing in states with either the NTR or trade war tariffs. The paths for the tariffs are distinguished by whether the change is viewed as permanent or uncertain. The uncertain path uses the baseline transition matrix. The mean simulation is the mean path over 100 simulations of the model.

Figure 5: Gap elasticities with possibility of across-the-board tariff increases



Notes: Figure shows coefficients β_t^{NNTR} and β_t^{TW} from (2). The coefficients are the elasticities of U.S. imports from China, relative to other countries, with respect to the tariff gap. Panel (a) plots the elasticities in the baseline model and a model where there is a chance of a 10p.p. across-the-board tariff increase starting in 2017. Panel (b) plots the elasticities in the baseline model and a model where there is a chance of a 10p.p. across-the-board tariff increase starting in 2022.

Table 1: Calibration summary

Parameter	Meaning	Value	Source/target
(a) Assigned			
r	Interest rate	4 pct.	Standard
ρ_z	Persistence of productivity	0.65	Alessandria et al. (2021a)
δ_0	Corr.(survival,productivity)	21.04	Alessandria et al. (2021a)
δ_1	Minimum death probability	0.023	Alessandria et al. (2021a)
$\tau_g(N)$	NNTR tariff	Varies by good	Data
$\tau_g(P)$	NTR tariff	Varies by good	Data
$\tau_g(W)$	Trade-war tariff	Varies by good	Data
$\theta_\gamma(g)$	Demand elasticity	Varies by sector	Soderbery (2018)
ρ_ξ	Prob. of keeping iceberg cost	0.87	Alessandria et al. (2021b)
ρ^N	Prob. of staying in NNTR	0.71	Alessandria et al. (2021b)
(b) Determined before the trade war			
$f_{\gamma(g)0}$	Entry cost	Varies by sector	Export participation rate
$f_{\gamma(g)1}$	Continuation cost	Varies by sector	Exit rate
$\xi_{\gamma(g)}$	High iceberg cost	Varies by sector	Incumbent premium
$\sigma_{\gamma(g)z}$	Productivity dispersion	Varies by sector	CV of log sales
(c) Determined during the trade war			
$1-\rho^P$	Prob. trade peace to NNTR	0.10	Δ NNTR-gap elasticity, 2018–2024
$\{1-\rho_t^W\}_{t=2018}^{2023}$	Prob. trade war to trade peace	Varies by year	Annual trade-war gap elasticities, 2019–2024

Notes: The estimates of the parameters in panel (b) are reported in Table 3.

Table 2: Chinese exporter dynamics statistics

	Sector	Export part.	Exit rate	Incumbent size prem.	Log CV exports
1	Food, beverage and tobacco	19	16	2.71	0.91
2	Textile, clothing, leather and footwear manufacturing	45	10	1.99	1.06
3	Wood and straw products	24	13	2.05	1.09
4	Paper and printing products	12	17	3.10	1.30
5	Energy products and chemicals	19	15	3.23	1.48
6	Rubber and plastic products	29	10	2.69	1.08
7	Non-metallic mineral products	16	18	2.26	0.85
8	Base metal manufacturing	12	21	3.96	1.15
9	Calendered metal manufacturing	29	10	2.48	1.24
10	Other machinery and equipment manufacturing industry	23	13	3.33	1.54
11	Computer, electronic and optical products	48	7	4.82	1.94
12	Electrical equipment manufacturing	32	10	3.35	1.55
13	Vehicle manufacturing	23	12	4.07	1.31
14	Furniture and other manufacturing	59	7	1.76	0.95
15	Non-manufacturing	28	13	2.99	1.25

Notes: The moments reported here are obtained using firm-level data from Chinese manufacturers. All moments refer to sectoral averages between 2004 and 2007. Export participation, in percent, is calculated as the number of firms with positive export sales over the total number of firms in a sector. The exit rate, in percent, is calculated as the number that exported in $t-1$ but not in t over the number of exporters in t. The incumbent size premium is calculated as the sales of incumbent firms over sales of new exporters. The last column is the log value of the coefficient of variation of sectoral export revenues. See Alessandria et al. (2021b) for a detailed description of the data.

Table 3: Sector-level model parameters

	Sector	$\theta_{\gamma(g)}$	$f_{\gamma(g)0}$	$f_{\gamma(g)1}$	$\xi_{\gamma(g)H}$	$\sigma_{\gamma(g)z}$
1	Food, beverage, tobacco	3.13	0.14	0.05	6.12	0.84
2	Textile, clothing, footwear	3.17	0.27	0.01	3.41	0.97
3	Wood and straw products	2.79	0.45	0.03	6.45	0.99
4	Paper, printing products	3.43	0.17	0.06	5.95	1.01
5	Energy products, chemicals	2.99	0.39	0.05	8.28	1.12
6	Rubber, plastic products	3.16	0.29	0.01	5.45	0.93
7	Non-metallic mineral products	2.85	0.15	0.07	7.13	0.85
8	Base metal manuf.	3.04	0.13	0.08	8.95	0.96
9	Calendered metal manuf.	2.73	0.54	0.01	7.15	1.06
10	Other machinery, equipment	3.74	0.27	0.03	4.59	1.11
11	Computer, electronic, optical	3.18	0.48	0.00	5.92	1.28
12	Electrical equipment manuf.	3.27	0.41	0.01	5.74	1.13
13	Vehicle manuf.	3.01	0.35	0.03	8.70	1.03
14	Furniture, other manuf.	3.26	0.29	0.00	2.48	0.95
15	Non-manufacturing	2.96	0.40	0.03	7.06	1.02

Table 4: Trade-policy innovations by administration

	Baseline		Perfect foresight	
	Trump	Biden	Trump	Biden
Expected duration (years)	1.8	6.0	1.0	4.7
Change in mean discounted tariff (%)	-0.4	1.1	-5.5	5.1
Change in applied tariff (%)	17.2	0.0	17.2	0.0

Notes: Expected duration is calculated as the inverse of the transition probability in 2020 for Trump and in 2024 for Biden. The change in the mean discounted tariff is based on changes in the mean discounted path from the start to end of each administration.

Appendix (For online publication)

In Appendix A, we include a timeline of key events in U.S.-China trade relations. In Appendix B, we show that the time-varying effects of the NNTR and trade-war gaps on China's exports to the United States, shown in Figure 3(a), are robust to a range of alternative approaches.

A Key dates in U.S.-China relations

10/1949 People's Republic of China is established.

12/1950 The trade embargo on China begins.

06/1971 The trade embargo is lifted and China gains access to U.S. markets at NNTR rates.

02/1972 Nixon visits China and issues the Shanghai Communiqué.

01/1979 The United States and China normalize relations with the Joint Communiqué on the Establishment of Diplomatic Relations.

04/1979 The Taiwan Relations Act is passed by Congress and signed by Carter.

02/1980 China gains access to U.S. markets at NTR rates under the Jackson-Vanik amendment.

11/1980 Reagan is elected President of the United States.

07/1982 The Six Assurances are sent by the United States to Taiwan.

08/1982 The Third Communiqué between the United States and China is issued.

05/1984 Reagan visits China.

06/1986 China applies for observer status to the GATT.

10/2000 Bill is signed granting China Permanent NTR status upon joining the WTO.

12/2001 China joins the WTO.

03/2018 Broad tariffs are proposed on Chinese goods.

02/2020 Phase one of the trade deal between the United States and China begins.

11/2020 Biden is elected President of the United States.

B Robustness: Empirics

Alternative fixed effects. In our baseline, we use a country-product (ig) fixed effect that captures trade relative to the year before the trade war. We use a good-time (gt) fixed effect to control for changes in U.S. demand for good g. These fixed effects are relatively standard in the literature. However, we also control for bilateral shocks at the sectoral level by including an i-HS sections-t fixed effect. In columns 2 and 3 of Table A1, we show that imposing less restrictive it or more restrictive i-HS 2-digit-t fixed effects yields similar results. In both cases, the time-varying path of the two gaps is very similar to our baseline (column 1), albeit slightly smaller in magnitude: the elasticities, on average, are 10 to 15 percent smaller than the baseline.

Alternative samples. Our baseline sample focuses on HS-6 goods that were exported to the United States in every year of our sample period and were not affected by the tariffs the Trump administration imposed on countries other than China.[12] Column 4 of Table A1 relaxes the first restriction and allows for the sample of goods to be unbalanced. Column 5 further relaxes both restrictions, thus including the full sample of goods. Overall, the time-varying paths of elasticities are very similar. Column 6 reports results when we define the year as beginning in January and ending in December. In this case, we reference the effects to the year 2017. As expected, the 2018 effect is small, as tariffs had only been in place for part of the year. Hence, the jump in elasticities from the first to the second year is even larger under our baseline July to June definition of a year. Nevertheless, between 2020 and 2023, the elasticity grows by almost 60 percent compared with the corresponding 45-percent growth between 2021 and 2024 in our baseline.

China supply effects and other destinations. In our baseline, we focus on U.S. imports only and use imports from other countries to control for U.S. good-specific demand shocks through the gt fixed effects. The results are virtually unchanged when we include Chinese exports to all 27 countries of the European Union ("EU-27") and include Chinese good-specific supply shocks (i.e., igt fixed effects). To do so, we aggregate over all other countries except China and use CIF import values since Eurostat does not report FOB values (and thus exclude controls for shipping costs). Column 7 of Table A1 reports the results. As a placebo test to further rule out unobserved supply shocks that spuriously correlate with the tariff gaps, we estimate (2) using EU-27 imports only. Column 8 shows there is no significant pattern in response to either of the gaps.

Gap measures. Our baseline trade-war gap, X_g^{TW}, is calculated as the log of the difference between the average applied tariff to China between 2020–2023 and 2013–2017, at the HS-6 level. The NNTR-gap, X_g^{NNTR} is calculated as the log of the difference between the six-digit NNTR rate and, again, the average applied tariff to China between 2013–2017, at the HS-6 level. The baseline HS-6 NNTR rate is the median HS-8 rate within the HS-6 subheading. Column 2 of Table A2 shows that the NNTR-gap elasticities increase slightly when we use the average over the HS-8 NNTR rates instead of the median. Column 3 considers the simple

[12] These were mostly steel and aluminum products targeted by the 2017 Section 232 tariffs and goods affected by the 2019 tariffs imposed on Mexico to deter migration. We obtain this set of goods from Fajgelbaum et al. (2020).

average over HS-10 products to compute the trade-war gap and the reference of the NNTR gap, computed as in column 2. The pattern is virtually the same as in the baseline.

Finer aggregation. Our baseline level of aggregation of goods is at the 6-digit HS level, the level commonly used in the literature (Handley et al., 2020). Columns 4 and 5 of Table A2 show that our results are similar to our baseline estimates when we use a more disaggregate definition of goods, at the 8- or 10-digit level, respectively.

Quarterly frequency. The quarterly data are better suited to capture changes in trade flows at a higher frequency but require controlling for seasonal fluctuations that potentially differ by good and source. Figure A1 plots the elasticity of imports to the trade-war gap in the quarterly data. The quarterly data are through the fourth quarter of 2023, although the fourth quarter of 2023 is based on data through November.

Figure A1: Tariff gap elasticities at the quarterly frequency

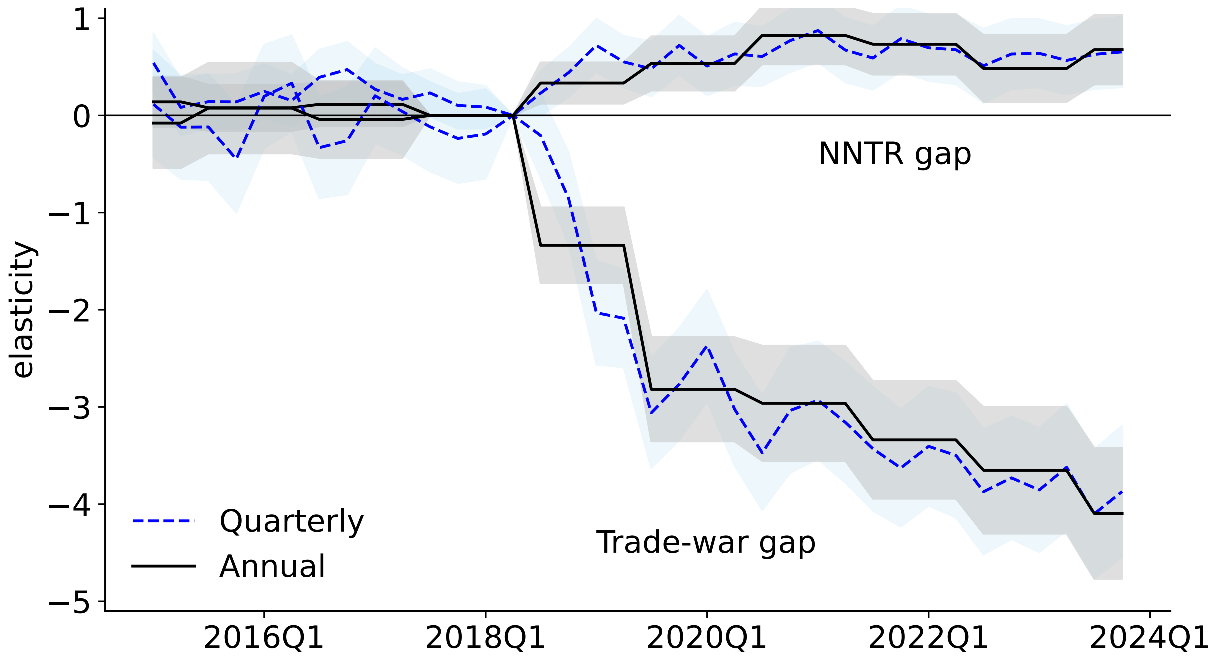


Table A1: Robustness: Gap elasticities

	Baseline	Alternative FEs		Alternative Samples			w/Chinese Exports to	
				Unbalanced	Full	Jan-Dec	US & EU-27	EU-27
Dep. Var. v_{igt}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}\{^{t=t'}_{j=\text{CHN}}\}X_g^{\text{TW}}$								
2015	-0.08	-0.19	0.06	-0.07	-0.18	0.02	0.37	-0.51^{*}
	(0.24)	(0.22)	(0.29)	(0.25)	(0.28)	(0.22)	(0.37)	(0.29)
2016	0.07	-0.03	0.20	0.22	0.18	-0.03	0.27	-0.30
	(0.24)	(0.22)	(0.28)	(0.25)	(0.27)	(0.17)	(0.34)	(0.26)
2017	-0.04	-0.06	-0.06	-0.01	0.08	0.00	-0.05	-0.15
	(0.20)	(0.18)	(0.25)	(0.21)	(0.21)	—	(0.29)	(0.20)
2018	0.00	0.00	0.00	0.00	0.00	-0.36^{**}	0.00	0.00
	—	—	—	—	—	(0.17)	—	—
2019	-1.34^{***}	-1.34^{***}	-1.37^{***}	-1.20^{***}	-1.16^{***}	-2.39^{***}	-1.29^{***}	-0.03
	(0.20)	(0.18)	(0.26)	(0.21)	(0.22)	(0.23)	(0.28)	(0.21)
2020	-2.82^{***}	-2.70^{***}	-2.75^{***}	-2.70^{***}	-2.72^{***}	-2.87^{***}	-2.59^{***}	-0.15
	(0.27)	(0.24)	(0.34)	(0.28)	(0.28)	(0.29)	(0.36)	(0.24)
2021	-2.96^{***}	-2.77^{***}	-3.08^{***}	-2.71^{***}	-2.61^{***}	-3.24^{***}	-3.23^{***}	0.39
	(0.30)	(0.27)	(0.37)	(0.31)	(0.30)	(0.29)	(0.39)	(0.27)
2022	-3.34^{***}	-3.02^{***}	-3.02^{***}	-3.11^{***}	-2.95^{***}	-3.27^{***}	-3.10^{***}	-0.04
	(0.31)	(0.27)	(0.39)	(0.32)	(0.32)	(0.31)	(0.42)	(0.30)
2023	-3.65^{***}	-3.31^{***}	-2.98^{***}	-3.50^{***}	-3.41^{***}	-3.81^{***}	-3.78^{***}	0.17
	(0.33)	(0.29)	(0.40)	(0.34)	(0.33)	(0.31)	(0.42)	(0.30)
2024	-4.09^{***}	-3.74^{***}	-3.38^{***}	-3.88^{***}	-3.77^{***}		-4.06^{***}	0.38
	(0.34)	(0.31)	(0.41)	(0.34)	(0.34)		(0.45)	(0.34)
$\mathbb{1}\{^{t=t'}_{i=\text{CHN}}\}X_g^{\text{NNTR}}$								
2015	0.14	0.22^{**}	0.24^{*}	0.17	0.00	0.12	0.21	-0.13
	(0.13)	(0.11)	(0.14)	(0.14)	(0.15)	(0.12)	(0.19)	(0.18)
2016	0.08	0.13	0.10	0.14	-0.02	0.19^{**}	0.07	-0.14
	(0.12)	(0.10)	(0.13)	(0.13)	(0.14)	(0.09)	(0.16)	(0.12)
2017	0.11	0.13	0.08	0.18	0.13	0.00	0.18	-0.10
	(0.12)	(0.09)	(0.12)	(0.12)	(0.12)	—	(0.16)	(0.11)
2018	0.00	0.00	0.00	0.00	0.00	0.09	0.00	0.00
	—	—	—	—	—	(0.10)	—	—
2019	0.33^{***}	0.23^{***}	0.39^{***}	0.37^{***}	0.31^{***}	0.54^{***}	0.27^{*}	0.01
	(0.11)	(0.09)	(0.12)	(0.11)	(0.12)	(0.13)	(0.15)	(0.11)
2020	0.53^{***}	0.45^{***}	0.42^{***}	0.65^{***}	0.62^{***}	0.72^{***}	0.52^{***}	-0.06
	(0.14)	(0.12)	(0.15)	(0.16)	(0.16)	(0.16)	(0.19)	(0.13)
2021	0.82^{***}	0.65^{***}	0.63^{***}	0.91^{***}	0.83^{***}	0.69^{***}	0.83^{***}	-0.09
	(0.15)	(0.13)	(0.16)	(0.16)	(0.15)	(0.15)	(0.20)	(0.14)
2022	0.73^{***}	0.50^{***}	0.63^{***}	0.68^{***}	0.66^{***}	0.59^{***}	0.74^{***}	-0.08
	(0.16)	(0.14)	(0.17)	(0.16)	(0.16)	(0.17)	(0.23)	(0.19)
2023	0.48^{***}	0.21	0.34^{*}	0.56^{***}	0.48^{***}	0.54^{***}	0.58^{**}	-0.19
	(0.18)	(0.15)	(0.19)	(0.18)	(0.17)	(0.18)	(0.23)	(0.17)
2024	0.68^{***}	0.49^{***}	0.44^{**}	0.70^{***}	0.60^{***}		0.63^{***}	-0.10
	(0.18)	(0.15)	(0.20)	(0.18)	(0.18)		(0.24)	(0.18)
log Shipping Cost	-2.54^{***}	-2.52^{***}	-2.59^{***}	-2.55^{***}	-2.56^{***}	-2.51^{***}		
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)		
gt, ig FEs	✓	✓	✓	✓	✓	✓		✓
i-HS Section-t FEs	✓			✓	✓	✓		✓
it FEs		✓						
i-HS2-t FEs			✓					
jgt, igt, jig FEs							✓	
ji-HS Section-t FEs							✓	
N	1,000,546	1,007,327	983,947	1,073,617	1,124,477	901,540	124,852	62,740
Adjusted R^2	0.88	0.88	0.88	0.88	0.88	0.88	0.95	0.95

Notes: The table reports estimates of (2). Columns 2 and 3 use less restrictive source-time and more restrictive source-HS2-time fixed effects, respectively. Column 4 uses an unbalanced panel and Column 5 uses the full sample, including goods that are part of trade disputes that do not discriminate only against China. Column 6 uses the conventional calendar year definition. Column 7 includes Chinese exports to an aggregate of the EU-27. Column 8 is a placebo test that uses only EU-27 imports. Standard errors clustered at the ig-level (and ijg level in column 7) are reported in parenthesis. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table A2: Robustness: Gap elasticities

		Alternative Gaps Measures		Good Level Aggregation	
	Baseline	Avg NNTR Gap	Simple Avg Gaps	HS-8	HS-10
Dep. Var. v_{igt}	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}\{^{t=t'}_{j=\text{CHN}}\}X_g^{\text{TW}}$					
t=2015	-0.08	-0.08	-0.07	0.35^{*}	0.37^{**}
	(0.24)	(0.24)	(0.25)	(0.21)	(0.18)
2016	0.07	0.08	0.09	0.50^{***}	0.55^{***}
	(0.24)	(0.24)	(0.24)	(0.19)	(0.17)
2017	-0.04	-0.04	-0.02	0.29^{*}	0.37^{**}
	(0.20)	(0.20)	(0.21)	(0.17)	(0.15)
2018	0.00	0.00	0.00	0.00	0.00
	—	—	—	—	—
2019	-1.34^{***}	-1.33^{***}	-1.39^{***}	-1.33^{***}	-1.18^{***}
	(0.20)	(0.20)	(0.21)	(0.18)	(0.15)
2020	-2.82^{***}	-2.81^{***}	-2.89^{***}	-2.94^{***}	-2.85^{***}
	(0.27)	(0.27)	(0.29)	(0.22)	(0.19)
2021	-2.96^{***}	-2.96^{***}	-3.02^{***}	-3.29^{***}	-3.13^{***}
	(0.30)	(0.30)	(0.32)	(0.24)	(0.21)
2022	-3.34^{***}	-3.34^{***}	-3.41^{***}	-3.28^{***}	-3.18^{***}
	(0.31)	(0.31)	(0.32)	(0.25)	(0.21)
2023	-3.65^{***}	-3.65^{***}	-3.72^{***}	-3.83^{***}	-3.68^{***}
	(0.33)	(0.33)	(0.35)	(0.26)	(0.23)
2024	-4.09^{***}	-4.09^{***}	-4.17^{***}	-3.88^{***}	-3.80^{***}
	(0.34)	(0.34)	(0.36)	(0.28)	(0.24)
$\mathbb{1}\{^{t=t'}_{j=\text{CHN}}\}X_g^{\text{NNTR}}$					
2015	0.14	0.16	0.18	-0.01	-0.05
	(0.13)	(0.14)	(0.14)	(0.11)	(0.09)
2016	0.08	0.10	0.11	0.00	-0.09
	(0.12)	(0.13)	(0.13)	(0.09)	(0.08)
2017	0.11	0.12	0.14	0.02	0.02
	(0.12)	(0.12)	(0.12)	(0.09)	(0.08)
2018	0.00	0.00	0.00	0.00	0.00
	—	—	—	—	—
2019	0.33^{***}	0.36^{***}	0.37^{***}	0.23^{***}	0.27^{***}
	(0.11)	(0.11)	(0.11)	(0.09)	(0.08)
2020	0.53^{***}	0.59^{***}	0.62^{***}	0.27^{**}	0.29^{***}
	(0.14)	(0.15)	(0.15)	(0.11)	(0.10)
2021	0.82^{***}	0.88^{***}	0.90^{***}	0.50^{***}	0.51^{***}
	(0.15)	(0.16)	(0.16)	(0.12)	(0.10)
2022	0.73^{***}	0.75^{***}	0.78^{***}	0.49^{***}	0.56^{***}
	(0.16)	(0.16)	(0.17)	(0.13)	(0.11)
2023	0.48^{***}	0.50^{***}	0.53^{***}	0.39^{***}	0.48^{***}
	(0.18)	(0.18)	(0.18)	(0.13)	(0.12)
2024	0.68^{***}	0.73^{***}	0.78^{***}	0.54^{***}	0.43^{***}
	(0.18)	(0.19)	(0.19)	(0.14)	(0.12)
log Shipping Cost	-2.54^{***}	-2.54^{***}	-2.54^{***}	-2.52^{***}	-2.52^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
gt, gt, ig FEs	✓	✓	✓	✓	✓
i-HS Section-t FEs	✓	✓	✓	✓	✓
N	1,000,546	1,000,546	1,000,546	1,216,526	1,713,591
Adjusted R^2	0.88	0.88	0.88	0.86	0.85

Notes: The table reports estimates of (2). Columns 2 and 3 consider alternative definitions of the gap—column 2 uses the average NNTR rate, instead of the median—and column 3 uses the simple averages of the pre- and post-war HS-10 tariffs, instead of the weighted average. Columns 4 and 5 define good g as an HS-8 and HS-10 code, respectively. Standard errors clustered at the ig-level are reported in parenthesis.* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.