Journal of International Economics 155 (2025) 104066

Contents lists available at ScienceDirect

Journal of International Economics

journal homepage: www.elsevier.com/locate/jie

Full length articles

Trade war and peace: U.S.-China trade and tariff risk from 2015–2050[☆]

George Alessandria[a,b], Shafaat Yar Khan[c], Armen Khederlarian[d], Kim J. Ruhl[b,e,*], Joseph B. Steinberg[f]

[a] University of Rochester, United States of America
[b] NBER, United States of America
[c] Syracuse University, United States of America
[d] Hunter College (CUNY), United States of America
[e] University of Wisconsin–Madison, United States of America
[f] University of Toronto, Canada

ARTICLE INFO

Dataset link: Data and Code for: Trade War and Peace: U.S.-China Trade and Tariff Risk from 2015-2050 (Original data)

JEL classification:
F12
F13
F14

Keywords:
Trade war
Trade liberalization
Trade-policy uncertainty (TPU)
Trade dynamics
Trade elasticity

ABSTRACT

We model trade policy as a Markov process. Using a dynamic exporting model, we estimate how expectations about U.S. tariffs on China have changed around the U.S.-China trade war. We find (i) 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 the expected mean future U.S. tariff on China rose more under President Biden than under President Trump.

1. Introduction

Donald Trump's election as U.S. President in 2016 raised questions about the future of U.S. trade-policy. Would he follow through on his campaign pledge to raise tariffs on China? If so, by how much? Would he shift China to the Non-Normal Trade Relations (NNTR) tariff schedule or choose something else? How long would these tariffs last? Would he reverse course quickly, as with President Nixon's import surcharge?[1] Or, would the tariffs remain in place for decades, as with President Truman's embargo on China? Once President Trump raised tariffs on China in 2018, the question of how long these tariffs would last was further

☆ We thank Yan Bai, Mark Bils, Fernando Leibovici, Nuno Limão, Marc Melitz, Carter Mix, and Michael Waugh for valuable discussions. We thank audiences at the Bank of Canada, FREIT, University of Houston, SED in Barcelona, University of Rochester, and 2024 NBER ITI for useful comments. Alessandria and Ruhl are grateful for support from the National Science Foundation, United States (award #2214852).

* Corresponding author at: University of Wisconsin–Madison, United States of America.
E-mail addresses: george.alessandria@rochester.edu (G. Alessandria), skhan78@syr.edu (S.Y. Khan), armen.khederlarian@hunter.cuny.edu (A. Khederlarian), ruhl2@wisc.edu (K.J. Ruhl), joseph.steinberg@utoronto.ca (J.B. Steinberg).

[1] In 1971, Nixon imposed a 10-percent import surcharge but removed it four months later.

https://doi.org/10.1016/j.jinteco.2025.104066
Received 9 October 2024; Received in revised form 18 February 2025; Accepted 20 February 2025
Available online 10 March 2025

complicated by the upcoming 2020 election and the subsequent Presidency of Joseph Biden. It remained an issue in 2024; in May, Biden renewed the tariffs and increased tariffs by 25 percent on almost 400 goods.

We answer these questions using disaggregated U.S. import data and a dynamic trade 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 using indirect inference.

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 began. 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 Normal Trade Relations (NTR) tariffs. This elasticity was stable in the three years before the Trump tariffs were put in place, suggesting there was no anticipatory response to these tariffs.[2]

Second, during the first two years of the trade war, the probability that tariffs would return to NTR levels was very high—more than 70 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 21 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, there existed a possibility of reverting to NNTR tariffs. This possibility still existed after China was granted Permanent NTR in 2001 and did not change with Trump's election, but it fell when the trade war began and a different tariff schedule was applied to China.[3] 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 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 WTO accession, which has been cited by Pierce and Schott (2016), Handley and Limão (2017), and others as evidence that this event eliminated policy uncertainty.

Our analysis yields a time-varying forecast of the path of trade and trade policy. We use this forecast to quantify the contributions of the Trump and Biden administrations to those paths. We find, even though Trump raised tariffs and Biden only maintained those tariffs, Trump lowered the discounted expected mean tariff by 5.3 percentage points while Biden raised it by 4.6 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 increases expected future tariffs.

Our analysis also highlights parallels between the trade reform in 1980 and the increase 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 cannot reject the hypothesis that these two episodes have the same trade-elasticity dynamics. This suggests that similar expectational dynamics were at work in both cases.

We contribute to the literature on the U.S.-China trade war surveyed in Fajgelbaum and Khandelwal (2022) and Caliendo and Parro (2023). Our novel approach builds on Alessandria et al. (2024b), henceforth AKKRS, by considering richer stochastic processes for trade policy and using them to forecast future trade dynamics. More broadly, our study relates to the trade-policy uncertainty literature, summarized by Handley and Limão (2022), and in particular, papers that use dynamic trade models to study the dynamics of trade policy.[4]

2. Reduced-form empirical analysis

We use U.S. import data from the U.S. Census Bureau (July 2014–June 2024, HS-6 level) and Eurostat import data for the 27 EU countries. We aggregate the EU countries into a single importer. For the United States and the European Union, China is treated as a separate exporter, while all other exporters are aggregated into a second group.[5] Imports of country j of good g from country i are denoted v_{ijgt}. We use a balanced sample – goods imported from China into the United States every year – and exclude goods that were affected by trade policies that were not China-specific. We use annual data to reduce concerns about stockpiling in advance of possible tariff changes.[6] To align with the timing of the trade war, we define a year as starting in July and ending in June.[7]

[2] Our findings suggest that there was no anticipation of a tariff increase, either correlated or uncorrelated with the tariffs imposed in 2018. See Sections 2.1 and 4.2 for further discussion.

[3] Similarly, Alessandria et al. (2024b) show the risk of losing NTR access did not materially change with the elections of Clinton, George W. Bush, or Obama. They argue that Reagan's 1981 election fundamentally changed the outlook on U.S. trade policy on China, raising the probability of losing NTR access.

[4] See Ruhl (2011), Alessandria et al. (2017), Handley and Limão (2017), Steinberg (2019), Alessandria et al. (2024a) and Hoang and Mix (2023).

[5] We use CIF import values, as Eurostat does not report FOB values.

[6] Alessandria et al. (2024a) find evidence of stockpiling in the 1990s prior to the July NTR renewal decision. Khan and Khederlarian (2021) show destocking occurred in advance of NAFTA tariff cuts.

[7] For example, 2019 covers 7/2018–6/2019. Our results are robust to using normal calendar years.

Fig. 1(a) plots the 25th, 50th, and 75th percentiles of the applied tariff distribution. The median tariff rises from about 3 percent in January, 2018 to 10 percent by October, 2018. By August, 2019, it is about 25 percent. The lower and upper quartiles increased by similar amounts.

For each good, we define the NTR tariff rate as the average applied tariff on China during 2015–2017. We construct two measures of good-specific tariff risk that represent the additional tariffs that Chinese imports face outside of the NTR regime.[8] The *trade-war gap* is the difference between the average applied tariff on China in 2020–2023 and the NTR tariff rate. The *NNTR gap* is the difference between the NNTR tariff rate, set by the Smoot-Hawley Tariff Act in 1930, and the NTR tariff rate. Formally,

$$X_g^j = \tau_g^j - \tau_g^{NTR}, \quad j = \{NNTR, TW\}. \tag{1}$$

Until the trade war, the NNTR gap represented the most relevant risk given the history of U.S. trade policy. Since the end of World War II, more than 20 countries were moved from NTR to NNTR tariffs or an outright embargo (see appendix for a list of countries). For example, in 2022, Russia and Belarus were shifted to NNTR tariffs following Russia's invasion of Ukraine. Numerous proposals have sought to remove China's permanent NTR status (e.g., 109th Congress, 2005; 118th Congress, 2023).

Fig. 1(b) plots the trade-war gap and NNTR-gap distributions. There are two key observations. First, the NNTR-gap distribution has a fatter tail and higher average, indicating that moving to NNTR status would be a bigger policy change than beginning the trade war. This difference plays an important role in the evolution of expected future tariffs since the trade war began. Second, the two gaps are approximately orthogonal, with a correlation of only −0.08. On average, goods that are exposed to one risk are not exposed to the other. The orthogonality allows us to separately identify the probabilities of these risks from the trade data.

2.1. Elasticities of trade to the trade-war gap and the NNTR gap

We extend the approach in AKKRS by measuring the dynamics of U.S. imports with respect to both the NNTR gap and the trade war gap,

$$\log v_{ijgt} = \sum_{t'=2015}^{2024} \left(\beta_t^{NTR} X_g^{NTR} + \beta_t^{TW} X_g^{TW} \right) \mathbb{1}_{\{i=\text{China} \,\wedge\, j=\text{US} \,\wedge\, t=t'\}} + \delta_{igt} + \delta_{jgt} + \delta_{ijg} + \delta_{ijht} + u_{ijgt}, \tag{2}$$

where δ_{ijg}, δ_{igt}, and δ_{jgt} are exporter-importer-good, exporter-good-time, and importer-good-time fixed effects, and δ_{ijht} is an exporter-importer-time fixed effect at the HS-Section level. As is common in event studies, we reference δ_{ijg} to the year before the trade war, 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 demand and supply shocks, time-invariant bilateral trade barriers, and aggregate shocks to exporting countries.

Fig. 1(c) plots the estimates of (2). The trade-war gap elasticity, β_t^{TW}, was statistically indistinguishable from zero throughout 2015–2017. Our interpretation of this finding is that the likelihood of a trade war did not change during this period. An alternative possibility is that a tariff increase was expected, but it was uncorrelated with the increase that occurred in 2018. The expected-but-uncorrelated tariff would not affect products with high trade-war gaps differently than products with low gaps, so it would show up as a change in the China-US-section-time fixed effects, $\delta_{\text{China},\text{US},h,t}$, rather than the trade-war gap elasticity. As Fig. 1(e) shows, however, these fixed effects were stable throughout the pre-war period, which casts doubt on this possibility. We discuss the (counterfactual) implications of this alternative possibility in Section 4.1.

During 2019–2020, the trade-war elasticity fell to about −2.5, likely reflecting the intensive-margin response to the increase in tariffs. From 2021 onward, it fell gradually by 1.8 points. There are two possible explanations for this growing substitution: (i) trade was gradually adjusting to the increase in tariffs, or (ii) the likelihood these tariffs would be reversed was falling. This is because the trade-war gap has two meanings: it represents the size of the past tariff increase at the onset of the trade war and it represents the potential future tariff reduction if the trade war ends. A structural model is needed to disentangle these two channels.

The NNTR-gap elasticity was also statistically insignificant during 2015–2017, indicating the probability of reverting to NNTR was also stable during this period. In 2019, it began to rise, and by 2024 was 0.6 points higher than before the trade war. This is notable because the NNTR gap is orthogonal to the trade-war gap; 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. 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 regimes. After the trade war began, the likelihood of reverting to NNTR fell and the uncertainty was now largely about moving between trade war and trade peace.

3. Structural model

Our empirical findings are inputs to the structural model we use to measure the dynamics of expectations about U.S. trade policy towards China and distinguish the trade effects of these dynamics from the gradual adjustment to the trade-war tariffs. The dynamic exporter model builds on Alessandria et al. (2021) and AKKRS by introducing a richer stochastic process for trade policy featuring multidimensional tariff risk.

[8] As discussed in the appendix, country-specific tariff risk will be absorbed in country-year fixed effects.

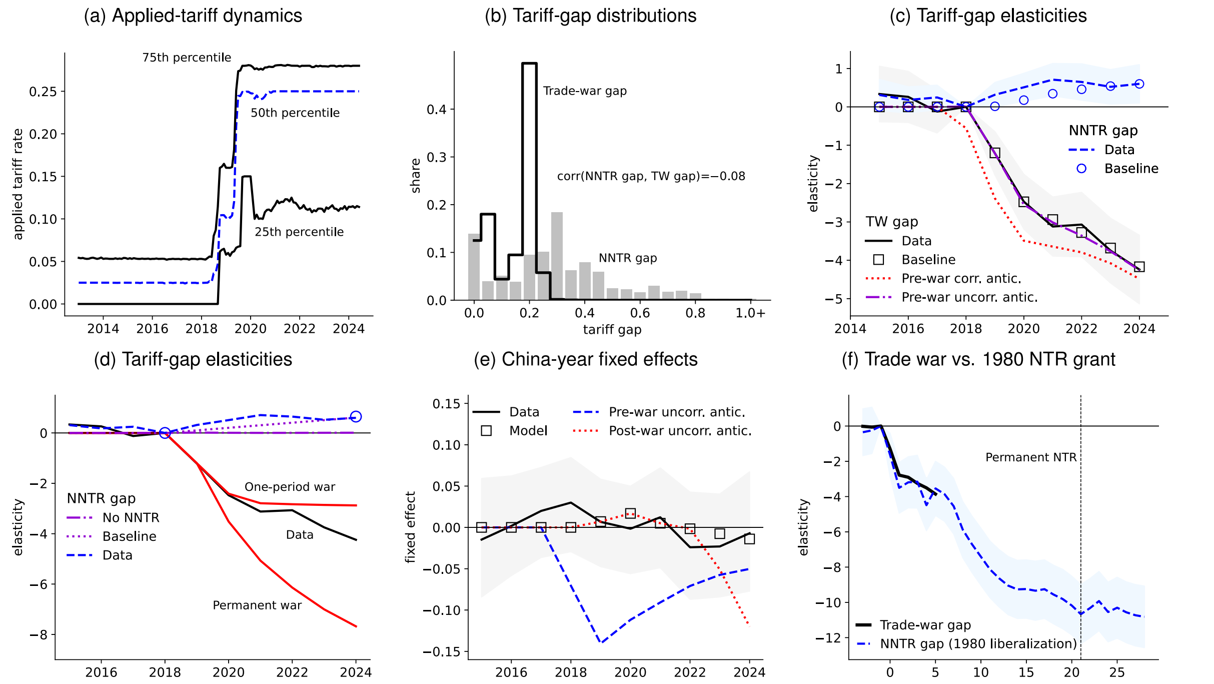

Fig. 1. Dynamics of U.S. trade policy and imports from China.
Notes: (a) Median and IQR of applied tariffs by year. (b) Trade-war gap and NNTR-gap distributions. (c) & (d) β_t^{NNTR} and β_t^{TW} from (2). (c) Data: 95-pct confidence intervals indicated by shaded areas. Baseline: calibrated model. Pre-war corr. antic.: model w/ anticipation of realized trade-war tariffs. Pre-war uncorr. antic.: model w/ anticipation of randomly-drawn tariffs uncorrelated with trade-war tariffs. (d) No NNTR: model w/ no chance of NNTR before trade war, i.e., $\omega_t(P,N) = 0\ \forall t$. One-period war: model w/ $\omega_t(W,W) = 0\ \forall t$. Permanent war: model w/ $\omega_t(W,W) = 1\ \forall t$. (e) Average China-HS-section fixed effect $(\frac{1}{H}\sum_{h=1}^{H}\delta_{\mathrm{CHN},h,t})$ from (2). Data, Baseline, Pre-war uncorr. antic.: same as in (c); confidence interval constructed using bootstrap method. Post-war uncorr. antic.: model w/ anticipation of additional randomly-drawn tariffs after trade war begins. (f) β_t^{TW} versus NNTR-gap elasticity from Alessandria et al. (2024b) normalized to zero in 1979.

3.1. Environment

There are G goods that correspond to the HS-6 goods in the data. 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 their current export participation. There are three trade-policy regimes: NTR, or *trade peace* (P), NNTR (N), and trade war (W). The probability of switching between regimes varies over time.

Trade policy. The good-level tariff, $\tau_g(s)$, depends on the current tariff regime, $s \in \{\text{P, N, W}\}$. The regime follows a time-varying Markov process with transition matrix

$$\Omega_t = \begin{bmatrix} \omega_t(P,P) & \omega_t(P,N) & \omega_t(P,W) \\ \omega_t(N,P) & \omega_t(N,N) & \omega_t(N,W) \\ \omega_t(W,P) & \omega_t(W,N) & \omega_t(W,W) \end{bmatrix}. \tag{3}$$

The main objects of interest are $\omega_t(P,N)$, the probability of switching from trade peace to NNTR, and $\omega_t(W,P)$, the probability of switching from trade war to trade peace. We make three assumptions about these objects. First $\omega_t(P,N)$ is constant before the trade war begins ($t < 2019$) and zero afterwards ($t \geq 2019$). This assumption is motivated by the increase in the NNTR-gap elasticity during the trade-war period. Second, the probability of a trade war starting, $\omega_t(P,W)$, is zero before the trade war begins ($t < 2019$). This assumption implies the tariff schedule in 2019 was unanticipated and is motivated by the stability of the trade-war gap elasticity during the pre-war period. Finally, we assume that year-to-year changes in Ω_t are unanticipated, i.e., firms expect the current matrix to remain in place going forward.

Trade costs. Firms pay variable costs of exporting (ξ) and fixed costs of entering (f_{g0}) and continuing in the U.S. market (f_{g1}). The variable cost takes three values ($\infty > \xi_{gH} > \xi_{gL}$) and follows a stationary 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. 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) to 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 firm's price, p,

$$d_{gt}(p, s) = \left(p\tau_g(s)\right)^{-\theta_g} D_{gt}, \tag{4}$$

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 is a monopolistic competitor that maximizes current-period profits by choosing its price, taking as given its residual demand and the wage, w,

$$\pi_{gt}(z, \xi, s) = \max_{p,\ell} p\, d_{gt}(p, \tau_g(s)) - w\ell \tag{5}$$

$$\text{s.t.} \quad z\ell \geq d_{gt}(p, \tau_g(s))\xi. \tag{6}$$

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

$$V^1_{gt}(z, \xi, s) = -f_g(\xi) + \frac{\delta(z)}{1 + r} \sum_{s'} \omega_t(s, s') \mathop{\mathbb{E}_t}_{z',\xi'} V_{g,t+1}\left(z', \xi', s'\right), \tag{7}$$

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

$$V^0_{gt}(z, \xi, s) = \frac{\delta(z)}{1 + r} \sum_{s'} \omega_t(s, s') \mathop{\mathbb{E}_t}_{z'} V_{g,t+1}\left(z', \infty, s'\right). \tag{8}$$

Given these objects, the value of the firm is

$$V_{gt}(z, \xi, s) = \pi_{gt}(z, \xi, s) + \max\left\{V^1_{gt}(z, \xi, s), V^0_{gt}(z, \xi, s)\right\}. \tag{9}$$

The break-even exporter has productivity $\bar{z}_{gt}(\xi, s)$ such that

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

This equation can be rewritten as

$$f_g(\xi) = \frac{\delta(\bar{z}_{gt}(\xi, s))}{1 + r} \sum_{s'} \omega_t(s, s') \left\{ \mathop{\mathbb{E}_t}_{z',\xi'} \left[V_{g,t+1}(z', \xi', s')\right] - \mathop{\mathbb{E}_t}_{z'} \left[V_{g,t+1}(z', \infty, s')\right] \right\}. \tag{11}$$

For the marginal firm, the fixed cost of exporting equals the expected gain in firm value from exporting in the future. Crucially, this object depends on the entire expected path of future tariffs, not only the current tariff rate.

3.3. Calibration

Our calibration has four stages. First, we map the model to the data by grouping HS-6 goods into 15 sectors. Second, we assign standard values 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 trade-policy transition probabilities to match our estimated dynamics of the trade-war and NNTR-gap elasticities. Table 1 provides an overview of the 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

$$\log a' = \rho_z \ln a + \varepsilon, \qquad \varepsilon \overset{iid}{\sim} N(0, \sigma^2_{\gamma(g)z}), \tag{12}$$

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 firm survival probability is $\delta(a) = 1 - \max\left[0, \min\left(e^{-\delta_0 a} + \delta_1, 1\right)\right]$, which implies higher-productivity firms are more likely to survive. We take the values of ρ_z, δ_0, and δ_1 from Alessandria et al. (2021). 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 AKKRS. Finally, we take the probability of switching from the NNTR regime to the trade-peace regime, $\omega_t(N, P)$, from AKKRS, as this parameter can only be identified by data from before 1980, when China had NNTR status. We assume this parameter is constant over time and set it to their estimate of 0.71.

Table 1
Calibration summary.

Parameter	Meaning	Value	Source/target
(a) Assigned			
r	Interest rate	4%	Standard
ρ_z	Persistence of productivity	0.65	Alessandria et al. (2021)
δ_0	Corr(survival, productivity)	21.04	Alessandria et al. (2021)
δ_1	Minimum death probability	0.023	Alessandria et al. (2021)
$\tau_g(N)$	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	Iceberg cost persistence	0.91	Alessandria et al. (2024b)
$\omega(N,P)$	NNTR persistence	0.71	Alessandria et al. (2024b)
(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	Export exit rate
$\xi_{\gamma(g)}$	High iceberg cost	Varies by sector	Incumbent premium
$\sigma_{\gamma(g)0}$	Entry cost	Varies by sector	CV of log sales
(c) Determined during the trade war (percent)			
$\omega(P,N)$	Prob. trade peace to NNTR	13.6	Δ NNTR-gap elasticity 2018–24
$\omega(W,P)_{2019}$	Prob. trade war to peace, 2019	74.5	Trade-war gap elasticity, 2020
$\omega(W,P)_{2020}$	Prob. trade war to peace, 2020	71.6	Trade-war gap elasticity, 2021
$\omega(W,P)_{2021}$	Prob. trade war to peace, 2021	34.8	Trade-war gap elasticity, 2022
$\omega(W,P)_{2022}$	Prob. trade war to peace, 2022	29.7	Trade-war gap elasticity, 2023
$\omega(W,P)_{2023}$	Prob. trade war to peace, 2023	20.8	Trade-war gap elasticity, 2024
(d) Implied trade-policy expectations (percent)			
τ^E_{2018}	Mean discounted tariff in 2018	12.7	Tariff data and estimated probabilities
τ^E_{2019}	Mean discounted tariff in 2019	7.2	Tariff data and estimated probabilities
τ^E_{2020}	Mean discounted tariff in 2020	7.3	Tariff data and estimated probabilities
τ^E_{2021}	Mean discounted tariff in 2021	9.8	Tariff data and estimated probabilities
τ^E_{2022}	Mean discounted tariff in 2022	10.4	Tariff data and estimated probabilities
τ^E_{2023}	Mean discounted tariff in 2023	11.9	Tariff data and estimated probabilities
τ^E_{2024}	Mean discounted tariff in 2024	11.9	Tariff data and estimated probabilities

Notes: The values of the parameters in panel (b) are reported in Table 2.

Table 2
Chinese exporter-dynamics statistics and sector-level model parameters.

Sector	Target statistics				Parameters				
	Exportpart. (%)	Exitrate (%)	Incumbentprem.	Log CVexports	$\theta_{\gamma(g)}$	$f_{\gamma(g)0}$	$f_{\gamma(g)1}$	$\xi_{\gamma(g)H}$	$\sigma_{\gamma(g)z}$
Food & beverage	19	16	2.71	0.91	3.09	0.06	0.08	4.47	0.82
Textile & clothing	45	10	1.99	1.06	3.17	0.07	0.07	2.84	1.02
Wood products	24	13	2.05	1.09	2.79	0.13	0.12	4.95	0.99
Paper & printing	12	17	3.10	1.30	3.43	0.09	0.09	4.60	1.00
Energy & chemicals	19	15	3.23	1.48	2.99	0.12	0.12	6.49	1.11
Rubber & plastics	29	10	2.69	1.08	3.16	0.07	0.07	4.35	0.92
Non-metallic mineral	16	18	2.26	0.85	2.85	0.08	0.09	5.05	0.83
Base metal	12	21	3.96	1.15	3.04	0.06	0.09	6.93	0.88
Calendered metal	29	10	2.48	1.24	2.73	0.12	0.10	6.30	1.03
Other machinery	23	13	3.33	1.54	3.74	0.09	0.09	3.74	1.13
Computer & electronic	48	7	4.82	1.94	3.18	0.11	0.10	5.90	1.29
Electrical equipment	32	10	3.35	1.55	3.27	0.10	0.09	4.84	1.14
Vehicles	23	12	4.07	1.31	3.06	0.08	0.08	7.20	0.98
Furniture & others	59	7	1.76	0.95	3.26	0.07	0.07	2.18	1.01
Non-manufacturing	28	13	2.99	1.25	2.97	0.10	0.10	5.55	1.00

Notes: Exporter-dynamics statistics are calculated using Chinese firm-level data (see Alessandria et al., 2024b, for a detailed description). All statistics are sector-level averages during 2004 and 2007. Export participation: number of firms with positive export sales divided by total number of firms. Exit rate: number of firms that exported in $t-1$ but not in t, divided by number of exporters in t. Incumbent size premium: average sales of incumbent exporters divided by average sales of new exporters. Log CV of exports: natural log of coefficient of variation of export sales.

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. 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, by sector, in the model and the data; the partial-equilibrium nature of our model allows us to calibrate each sector independently. The empirical moments and the estimated parameters are reported in Table 2.

Parameters determined during the trade war. We calibrate the probabilities of switching trade-policy regimes to match our estimates of the trade-war gap and NNTR-gap elasticities. Given the assumption that NNTR is no longer possible once the trade war starts, the probability of switching from trade peace to NNTR during the pre-war period, $\omega_{t<2019}(P, N)$, 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, $\omega_t(W, P)$, is identified by the dynamics of the trade-war gap elasticity in the subsequent periods. For example, $\omega_{2019}(W, P)$ is identified by the trade-war gap elasticities from 2020 onward and $\omega_{2020}(W, P)$ by the elasticities from 2021 onward.

4. Results

First, we discuss our model's ability to account for the trade dynamics around the trade war and the path of trade-policy expectations implied by these dynamics. Second, we study the implications of our estimates for the future of U.S.-China trade. Finally, we relate the current substitution patterns and risks to the trade liberalization in 1980.

4.1. Dynamics of trade flows and trade policy

Fig. 1(c) shows that the model captures the dynamics of both the trade-war gap and NNTR-gap elasticities. The former falls sharply between 2018–2020, then continues to fall gradually over the following four years. The latter rises after 2018, albeit more slowly in the model than in the data; the model reproduces the cumulative change. Fig. 2(a) plots our main finding: the implied probabilities of switching between trade-policy regimes. Before the trade war began, the probability of moving from trade peace to NNTR was 13.6 percent. Once the trade war began, the probability of returning to trade peace was 74.5 percent in 2019 and 71.6 percent in 2020, but then fell sharply, reaching 20.8 percent in 2024.[9]

Fig. 1(d) provides some intuition into the identification of these probabilities. The line labeled "No NNTR" depicts the evolution of the NNTR-gap elasticity when the probability of moving from trade peace to NNTR is constant at zero. The NNTR-gap elasticity barely changes; the slight increase is from the small negative correlation between the two gaps. In the baseline calibration, where the probability of moving to NNTR falls at the onset of the trade war, the line rotates upward and we can now match the growth in trade in these products. This reaffirms the idea that NNTR continued to be viewed as a possibility after China was granted PNTR.

Turning to how the persistence of the trade war affects trade dynamics, the line labeled "permanent war" shows how the trade-war gap elasticity evolves if the trade war is permanent, and the line labeled "one-period war" shows how this elasticity evolves if firms always believe the trade war will end in the next period. In the permanent case, the elasticity falls further over time as export participation in goods with high trade-war gaps decreases more. In the temporary case, the elasticity is flat after 2020 because export participation is unchanged; the movements in the elasticity in 2019 and 2020 are due purely to the intensive-margin response to the two rounds of trade-war tariffs. The differences between these two extremes and the calibrated model reflect changes in policy expectations over time, which determine investments in market access.

We assumed that the trade war was a surprise. Here, we use our model to study trade dynamics when firms anticipate the trade war.[10] In Fig. 1(c), the line labeled "Pre-war corr. antic." shows, if firms believed ahead of time that the trade war was possible ($\omega_t(P, W) > 0$ for $t < 2019$), the trade-war gap elasticity would have fallen earlier. This anticipation is not in the data. Alternatively, as discussed in Section 2, if firms thought tariffs could rise, but did not anticipate the trade-war tariffs specifically (e.g., they anticipated a common tariff increase on all products), the anticipatory effect is captured in the country-section-time fixed effects rather than the gap elasticities. The line labeled "Pre-war uncorr. antic." in Fig. 1(e) shows these fixed effects would fall before the trade war in this scenario, whereas there are no statistically significant movements in the data or our baseline model.

Similarly, we can model how trade would have evolved if firms anticipated further tariff increases after the trade war started. If these increases were expected to be correlated with the current trade-war tariffs, the effect would show up as a downward movement in the trade-war gap elasticity, but this movement would be small and would not materially affect our estimates of the probability of ending the trade war. If additional tariff increases were expected to be uncorrelated with the trade-war tariffs, Fig. 1(e) shows that the effect would again appear as a decline in the China-year fixed effects ("Post-war uncorr. antic."). There is no evidence of this decline in the data, either.

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

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

Fig. 2(b) plots the probability of being in the trade-peace regime in the future, 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 (about 54 percent). The conditional probability of being in trade-peace regime in 2025 is 21 percent, and this probability rises over time, eventually surpassing the unconditional probability in 2031. In the long-run, there is a 60 percent probability that China is in the trade-peace regime.

[9] This figure is very similar to the probability of moving from the NNTR regime to trade peace estimated in Alessandria et al. (2024b).

[10] The appendix contains more details on our experiments with anticipation.

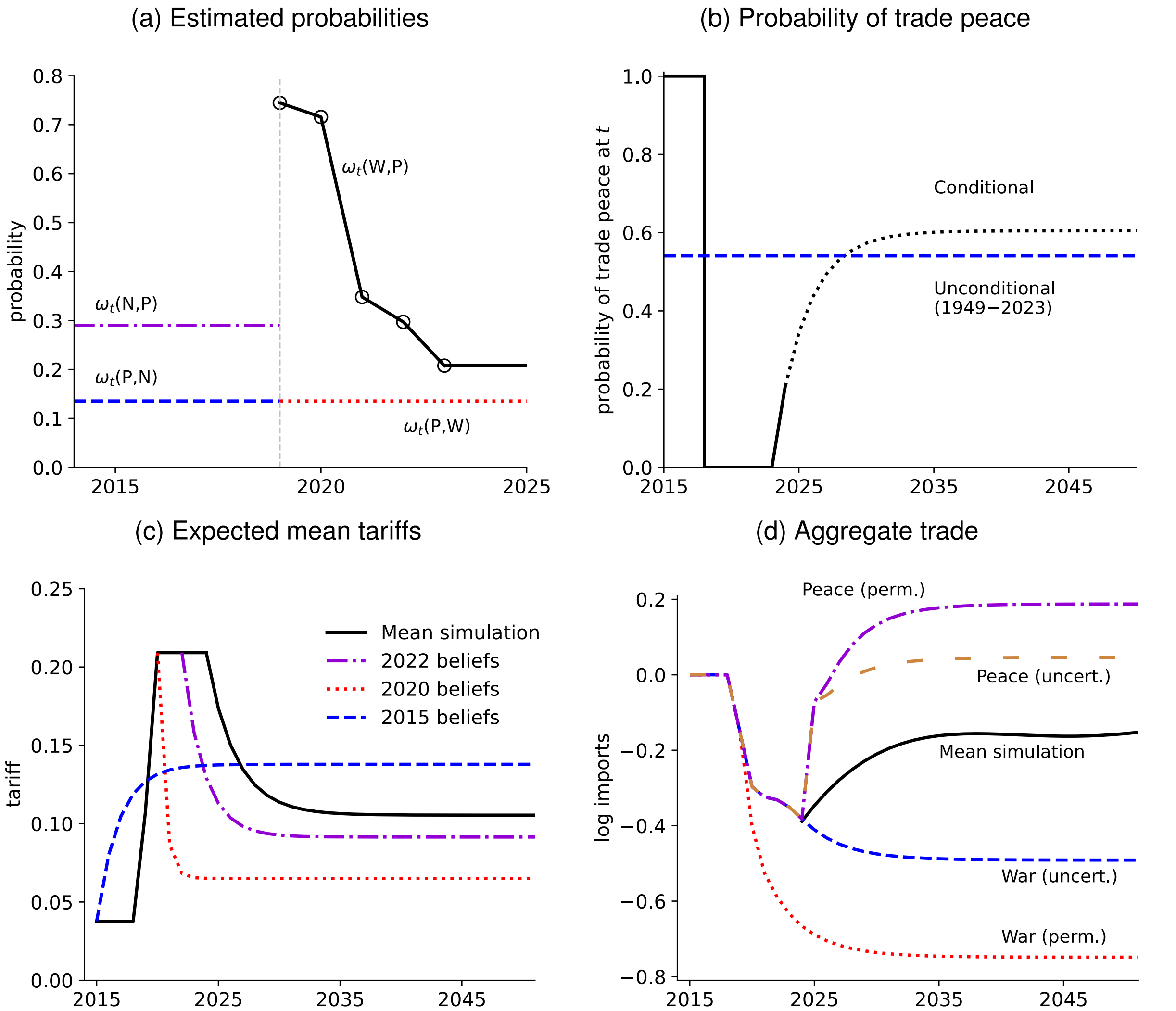

Fig. 2. Model projections.
Notes: (a) Trade-policy transition probabilities. (b) Probability of trade peace. Conditional: historical during 2015–2024 and model forecasts from 2025 onward. Unconditional: share of years in trade peace during 1949–2023. (c) Expected path of tariffs in 2015 versus 2020, alongside mean realized path from model simulations. (d) Aggregate trade projections under different scenarios. War (uncertain): remain in trade war with estimated transition matrix. Peace (uncertain): switch to trade peace in 2025 with estimated transition matrix. War (certain): remain in trade war with no chance of peace. Peace (certain): switch to trade peace in 2025 with no chance of war. Mean simulation: average path over 100 simulations of the model.

Fig. 2(c) plots the evolution of the expected mean tariff. The "mean simulation" line is the average NTR 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, starting from the trade-war regime, and similar for the "2022 beliefs" line. The former falls sharply, reflecting the high initial probability of ending the trade war, whereas the latter falls more slowly and converges to a higher level, reflecting the declining probability of trade peace as the trade war continues. 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 higher than the post-war long-run average because the NNTR regime has higher average tariffs than the trade-war regime.

We can use our results to compare the changes in trade policy during the Trump and Biden administrations with the changes in policy expectations. We calculate two measures of policy expectations for each President: the expected duration of the trade war and 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 Presidency. The mean discounted expected tariff is

$$\tau_t^E = \mathbb{E}_t \frac{1}{G} \sum_{g=1}^{G} \frac{r}{1+r} \left(\sum_{k=t}^{\infty} (1+r)^{t-k} \tau_g(s_k) \right). \tag{13}$$

While the average tariff rises by 17.1 percentage points during the Trump administration, the mean discounted tariff falls by 5.3 percentage points, because the trade-war regime has a lower average tariff than the NNTR regime and the trade war is expected to end quickly during 2019–2020. At the end of the Trump presidency, the expected duration of the trade war is 1.4 years. Under Biden, the average applied tariff does not change, but the mean discounted tariff increases by 4.6 percentage points because the likelihood of ending the trade war falls during 2021–2024. The expected duration of the trade war in 2024 is 4.8 years.

What do our estimates imply about the future dynamics of U.S. imports from China? In Fig. 2(d), we plot aggregate trade under different scenarios. In the ‘‘uncertain trade war’’ scenario, the trade war continues indefinitely but firms continue to believe that the trade war has a 21 percent chance of ending. In this scenario, trade declines gradually as Chinese exporters adjust to the trade-war tariffs and the decreasing probability of trade peace. In the long run, the aggregate level of U.S. imports from China is 0.49 log points 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, although firms believe it has a 14 percent chance of restarting. 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 reaching the NNTR regime.

In the ‘‘permanent trade war’’ scenario, firms initially operate under the original pre-trade-war transition matrix, but when the trade war starts, they believe it will be permanent. On impact, trade falls by the same amount as in the baseline trade-war scenario, then continues to fall further. In the long run, aggregate trade stabilizes 0.75 log points below the pre-trade-war level – double the baseline scenario's decline – despite identical tariff paths.

At the other extreme, in the ‘‘permanent trade peace’’ scenario, the economy follows the baseline case until 2025, at which point the trade war ends and is expected to never resume. We assume that returning to the NNTR regime is impossible; 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, but grow more later, ultimately converging to 0.19 log points 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 and the possibility of moving to the NNTR regime.

Our last approach considers the distribution of possible future outcomes by simulating a large number of potential trade-policy sequences, $\{s_t\}_{t=2025}^{\infty}$, holding the policy transition matrix constant, i.e., $\Omega_t = \Omega_{2023}$ for $t = 2024, \dots, \infty$. In Fig. 2(d), we plot the mean path of U.S. imports from China in these simulations. On average, trade grows from its 2024 level, but falls relative to its 2018 level by 0.16 log points in the long run.

4.3. 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 NTR, lowering tariffs dramatically, subject to annual renewal by the U.S. President. Here, we show 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 expectations in the two episodes.

AKKRS use a version of (2) to estimate annual NNTR-gap elasticities during 1974–2008. Fig. 1(f) plots their estimated NNTR-gap elasticities against our trade-war gap elasticities, each normalized to zero in the year before the relevant reform. The elasticity dynamics in the two episodes are similar. In both cases, five years following the tariff change the trade elasticity was 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 rose to almost 11 in 2001, when China joined the WTO.

AKKRS attribute part of the slow adjustment of U.S. imports from China following the 1980 liberalization to low 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 from investing in U.S. market access, but as the reform gained credibility, Chinese firms invested in market access, and trade grew rapidly. A similar adjustment is underway 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 rise, we should expect to see further substitution away from Chinese goods.

The 1980 trade liberalization can help us understand the trade war. 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 followed the normalization of relations with China by President Carter and severed diplomatic relations with Taiwan. 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 issue in the subsequent Carter-Reagan election. Reagan campaigned on restoring relations with Taiwan and, in the early stages of his presidency, took steps in this direction. Only with Reagan's visit to China in 1984 did the relationship become more credible.

Similarly, the 2018 reform was a substantial shift in trade policy on imports from China. Nearly every U.S. presidential election since Carter-Reagan discussed trade restrictions on China, but ended with 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 entered office, the trade-war tariffs have remained and industrial policy, in the Chips and Science Act and the Inflation Reduction Act in 2022, further restricted imports from China. In May 2024, in the review of the trade-war tariffs, the Biden administration proposed increasing tariffs by 25 percent on almost 400 goods; most went into effect in September.

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

5. Conclusion

The trade war between the United States and China that began in 2018 demonstrated that China's Permanent Normal Trade Relations status did not eliminate trade-policy risk, and that the nature of this risk had fundamentally changed. At the beginning of the trade war, the expected path of future tariffs fell because the trade-war tariffs were expected to be quickly reversed and the likelihood of Non-Normal Trade Relations had diminished. As the trade war continued, expected tariffs grew.

Our estimation of the trade-policy process leverages heterogeneity across goods in observed tariffs, tariff risk, and trade dynamics. We interpret this heterogeneity using a model of forward-looking firms. Alternative processes that allow for other risks could yield different model outcomes, but should be disciplined by the dynamics of trade to these new and old risks. Likewise, alternative models could be used to discipline the trade-policy process, but these should be forward-looking, dynamic models; static models are silent on trade-policy expectations and are inconsistent with the gradual substitution patterns in U.S. imports since the onset of the trade war. Existing work on the aggregate effects of trade policy in static versus dynamic models (Alessandria et al., 2021; Mix, 2023) suggests a need to revisit the aggregate effects of the trade war. Our estimates of the stochastic path of trade policy could be an input to such an analysis.

The dynamics of U.S.-China trade disintegration resemble the dynamics of integration following the normalization of relations in 1980, but in reverse. Owing to geopolitical considerations and political turnover in each country, 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.

Declaration of competing interest

All authors have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. George Alessandria received support from the National Science Foundation, award #2214852.

Kim J. Ruhl is a co-editor of the Journal of International Economics and was not involved in the editorial review or the decision to publish this article. Ruhl received support from the National Science Foundation, award #2214852.

Joseph B. Steinberg is an associate editor of the Journal of International Economics and was not involved in the editorial review or the decision to publish this article.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jinteco.2025.104066.

Data availability

Data and Code for: Trade War and Peace: U.S.-China Trade and Tariff Risk from 2015-2050 (Original data) (Mendeley Data)

References

109th Congress, 2005. To withdraw normal trade relations treatment from the products of the People's Republic of China. URL https://www.congress.gov/bill/109th-congress/house-bill/728/text.

118th Congress, 2023. China trade relations act of 2023. URL https://www.congress.gov/bill/118th-congress/senate-bill/125.

Alessandria, George, Choi, Horag, Lu, Dan, 2017. Trade integration and the trade balance in China. IMF Econ. Rev. 65 (3), 633–674, URL https://ideas.repec.org/a/pal/imfecr/v65y2017i3d10.1057_s41308-017-0036-2.html.

Alessandria, George, Choi, Horag, Ruhl, Kim J., 2021. Trade adjustment dynamics and the welfare gains from trade. J. Int. Econ. 131, 103458, URL https://www.sciencedirect.com/science/article/pii/S0022199621000350.

Alessandria, George, Khan, Shafaat Y., Khederlarian, Armen, 2024a. Taking stock of trade policy uncertainty: Evidence from China's pre-WTO accession. J. Int. Econ. 150, 103938, URL https://www.sciencedirect.com/science/article/pii/S0022199624000655.

Alessandria, George, Khan, Shafaat Y., Khederlarian, Armen, Ruhl, Kim J., Steinberg, Joseph B., 2024b. Trade-policy dynamics: Evidence from 60 years of U.S.-China trade. J. Political Econ. Accepted..

Caliendo, Lorenzo, Parro, Fernando, 2023. Lessons from US–China trade relations. Annu. Rev. Econ. 15 (1), 513–547, arXiv:https://doi.org/10.1146/annurev-economics-082222-082019.

Das, Sanghamitra, Roberts, Mark J., Tybout, James R., 2007. Market entry costs, producer heterogeneity, and export dynamics. Econometrica 75 (3), 837–873.

Fajgelbaum, Pablo D., Khandelwal, Amit K., 2022. The economic impacts of the US–China trade war. Annu. Rev. Econ. 14 (1), 205–228, arXiv:https://doi.org/10.1146/annurev-economics-051420-110410.

Handley, Kyle, Limão, Nuno, 2017. Policy uncertainty, trade, and welfare: Theory and evidence for China and the United States. Am. Econ. Rev. 107 (9), 2731–2783.

Handley, Kyle, Limão, Nuno, 2022. Trade policy uncertainty. Annu. Rev. Econ. 14 (1), 363–395, arXiv:https://doi.org/10.1146/annurev-economics-021622-020416.

Hoang, Trang, Mix, Carter B., 2023. Trade war, adjustment dynamics, and expectations. Mimeo.

Khan, Shafaat Y., Khederlarian, Armen, 2021. How does trade respond to anticipated tariff changes? Evidence from NAFTA. J. Int. Econ. 133, 103538.

Mix, Carter B., 2023. The dynamic effects of multilateral trade policy with export churning. Internat. Econom. Rev. 64 (2), 653–689, URL https://EconPapers.repec.org/RePEc:wly:iecrev:v:64:y:2023:i:2:p:653-689.

Pierce, Justin R., Schott, Peter K., 2016. The surprisingly swift decline of US manufacturing employment. Am. Econ. Rev. 106 (7), 1632–1662.

Ruhl, Kim J., 2011. Trade dynamics under policy uncertainty. Am. J. Agric. Econ. 93 (2), 450–456.

Ruhl, Kim J., Willis, Jonathan L., 2017. New exporter dynamics. Internat. Econom. Rev. 58 (3), 703–726.

Soderbery, Anson, 2018. Trade elasticities, heterogeneity, and optimal tariffs. J. Int. Econ. 114, 44–62.

Steinberg, Joseph B., 2019. Brexit and the macroeconomic impact of trade policy uncertainty. J. Int. Econ. 117, 175–195.