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Trump, China, and the Republicans

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Abstract

The Republican Party has been the party most supportive of free trade in American politics for half a century. President Donald Trump, who is a Republican, holds a different stance from his party on free trade. We assess how Trump's China tariffs in mid-2018 impacted the performance of his party in its midterm house elections later that year. We construct a measure of each county's exposure to Trump's China tariffs and merge that with the Republican share of votes in the county. We find that the counties heavily exposed to the tariffs were more supportive of their Republican house candidates. This association is stronger and causal in counties that previously voted for Democratic politicians. The Republican Party, despite losing its majority in the house, would have lost more seats without Trump's China tariffs.

JEL codes: F13, D72, P16

1 Introduction

The two major political parties in the US, the Republican Party and the Democratic Party, switch their stances on free trade from time to time. The most recent switch occurred in the last century, when the Republicans, who proposed the Smoot-Hawley Tariff Act and sparked a trade war among industrialized economies in the 1930s, became the party more supportive of free trade in the second half of the century. The Republican-trade relationship is now reaching another critical moment. Donald Trump, who is affiliated with the Republican Party and was elected as the 45th US president, used his executive power to raise tariffs on US imports from China in mid-2018. The congressional elections in November 2018, known as midterm elections since they occurred halfway through a president's four-year term, was the first political appraisal by American voters of the Republican turnabout on trade policies.

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This study examines how Trump's China tariffs impacted the outcome of midterm elections for Republican house candidates. We construct a measure of each US county's exposure to Trump's China tariffs using the county's employment composition. We find that the Republican Party received more support in 2018 than in 2016 in counties with a higher exposure to Trump's China tariffs. This association applies across the political spectrum of the country, including states that were either "blue" or "red" in previous presidential elections and congressional districts with either Democratic or Republican incumbents.

We next identify the underlying causality. Trump's China tariffs specifically targeted the Chinese government's Made-in-China 2025 Initiative (hereafter, MIC2025). The MIC2025, released by the Chinese government in 2015 as a guide for domestic investments, favored high-tech industries with strategic future value, such as aircraft, robots, and new energy automobiles. This initiative served as a critical motivation for Trump's China tariffs, a point made clear by the Trump administration when it announced the tariffs. As a proposal not yet developed by the Chinese government into industrial or trade policies, the MIC2025 influenced the target product list of Trump's China tariffs, but had little reason to affect county-level ballots through other channels on the US side.

By instrumenting county-level China tariff exposure with county-level MIC2025 exposure, we find that a higher exposure to Trump's China tariffs raises local support for Republican house candidates, a causal effect that is mainly driven by counties that previously voted for Democratic politicians. The impact of Trump's China tariffs on Republican house candidates was statistically insignificant in counties that tended to vote for Republican politicians in the past. This indicates that local momentum promoting a hawkish China policy had been, at least partly, absorbed into the local votes for Republican politicians in 2016, and thus a strict China policy made by Republican politicians — the Republican president, in this case — barely generated additional support from those places. The additional political gains actually came from where voters leaned towards Democratic politicians in the past.

Notice that the political gains for the Republicans estimated in this paper have accounted for the political feedback given by local voters when China retaliated by imposing additional tariffs on US products. Our estimated effect is a net effect between a positive direct effect (voters rewarded Republicans for benefits received from Trump's China tariffs) and a potentially negative indirect effect (voters blamed Republicans for their losses from China's retaliation against the US). Separating the direct effect from the indirect effect is not our main research interest. We propose an exploratory approach to isolating the direct effect, the application of which suggests even larger political gains for Republicans when the indirect effect is excluded.

Lastly, we conduct a counterfactual analysis by subtracting the estimated political gains for Republican house candidates from the county-level votes they received to examine how the midterm election outcome would have changed without Trump's China tariffs. By aggregating county-level counterfactual results to the congressional district level, we find that Republicans, despite losing seats and its majority in the house at the midterm, would had lost even more seats without Trump's China tariffs. Specifically, they would have lost two to four congressional districts that they narrowly won at the midterm, and would have been unable to flip one to two previously Democratic seats that switched Republican at the midterm.

International trade, although beneficial to each participating nation as a whole, does not necessarily make every citizen in the participating nations better off. Most trade policies are contentious as they create both winners and losers at the same time. Gains and losses from international trade have been extensively documented to influence policy making (Blonigen and Figlio, 1998; Baldwin and Magee, 2000; Conconi, Facchini, and Zanardi, 2012, 2014) as well as the elections of politicians (Autor, Dorn, Hanson, and Majlesi, 2020; Che, Lu, Pierce, Schott, and Tao, 2016; Conconi, Facchini, Steinhardt, and Zanardi, 2019; Dippel, Gold, and Heblich, 2015; Feigenbaum and Hall, 2015; Freund and Sidhu, 2017; Jensen, Quinn, and Weymouth, 2017; Mayda, Peri, and Steingress, 2016). Trade wars exhibit the most intense conflicts of interests in an international political setting. In a trade war, not only nations act strategically to attack one another, but interest groups within each nation also fight against each other to influence their nation's response strategy. The trade war initiated by the Trump administration is unique in its political significance. As mentioned above, it was launched by a Republican president after the Republican Party's half-century long friendliness towards free trade. Moreover, the China tariffs were only part of Trump's trade war. His trade war, which set not only China but also multiple industrialized economies as targets, is reminiscent of the last global trade war set in motion by the Republican-sponsored Smoot-Hawley Tariff Act in the 1930s.

Empirical studies related to trade wars always entail enormous challenges in identification. The decision made by a country to open fire on foreign products is usually accompanied by following strategic moves of the country on economic and political issues, with retaliations by trade partners expected and taken into account. These actions are all endogenous for any government involved in a trade war. Researchers have come up with various approaches to addressing this endogeneity. Among the few existing empirical studies on the midterm elections of 2018, Fetzer and Schwarz (2019) and Chyzh and Urbatsch (2019) chose to examine how retaliations by foreign countries, rather than domestic trade policies, affected domestic elections, while Blanchard, Bown, and Chor (2019) opted for a wide coverage of election outcome determinants in their study, including US tariffs, agricultural subsidies, and healthcare reform made by the Trump administration. These studies pursue data variations related to foreign trade policies and non-trade policies for clean identification.

Our study distinguishes itself from the existing studies by pursuing domestic (US) trade policy variations targeting a single foreign country. Because of our sole focus on the China tariffs, we are able to use MIC2025 to formulate an instrumental strategy that identifies how Trump's tariffs causally impacted the Republicans' midterm. We are interested in neither how other countries responded to Trump's tariffs nor other policies of the Trump administration. Our study is actually more relevant to the "China Syndrome" literature than to the trade war literature. The China Syndrome literature, pioneered by Autor, Dorn, and Hanson (2013), Acemoglu, Autor, Dorn, Hanson, and Price (2016), and Pierce and Schott (2016, 2020), establishes that US imports of Chinese products causally threatened its domestic employment to varying degrees owing to different local industrial composition. Motivated by their findings, we expect voters to opine using their votes in local elections. Trump attempted with his China tariffs to address the country's China Syndrome. The US House of Representatives provides representation proportional to local population. The midterm house elections of November 2018, immediately following Trump's 2018 round of China tariffs, allow us to assess the political popularity of Trump's attempt.

Our research interest also lies in the role of China in American politics. China became a card to play in the US political arena far earlier than when it became the second largest economy in the world, as concisely summarized by Carpenter (2012):

> *Reagan repeatedly criticized President Jimmy Carter for establishing diplomatic relations with Beijing. Bill Clinton excoriated the "butchers of Beijing" in the 1992 campaign and promised to stand up to the Chinese government on both trade and human rights issues. Candidate Barack Obama labeled President George W. Bush "a patsy" in dealing with China and promised to go "to the mat" over Beijing's "unfair" trade practices.* [...]
>
> *Republican presidential nominee Mitt Romney has denounced the Obama administration for being "a near-supplicant to Beijing" on trade matters, human rights and security issues. An Obama ad accuses Romney of shipping U.S. jobs to China through his activities at the Bain Capital financier group, and Democrats charge that Romney as president would not protect U.S. firms from China's depredations.*

Interestingly, nearly all recent US presidents, once elected, adopted a pragmatic — even amenable — approach towards China, which largely contributed to China's continual growth to become the second largest economy after the US. A natural question thus arises to whether a high-pitched voice followed by a low-pitched inaction on China issues was a strategy used by American politicians to maximizing their total gains, including but not limited to winning elections. Donald Trump did not sound particularly hawkish on China issues during his campaign, but became a China-fighter after being elected. As shown in our paper, his China card, played in a manner contrasting to his Republican as well as Democratic predecessors, brought political gains and even garnered some political support that would have belonged to the Democrats. In this regard, our findings contribute to the economic understanding of American politics by documenting the political gains, which are less ambiguous than the economic gains, from implementing strict policies toward China.

The rest of the paper is organized as follows. In Section 2, we describe our data, including their sources, construction, and summary statistics. In Section 3, we report our findings, including baseline results (OLS and 2SLS) and their robustness checks. In Section 4, we discuss competing explanations of our findings. In Section 5, we conduct a counterfactual study on the midterm house elections of 2018. In Section 6, we conclude.

2 Data

2.1 Trump's China Tariffs

Donald Trump, inaugurated as the 45th US president on January 20, 2017, instructed the United States Trade Representative (USTR) on August 14, 2017 to investigate whether China "implemented laws, policies, and practices and has taken actions related to intellectual property, innovation, and technology that may encourage or require the transfer of American technology and intellectual property to enterprises in China or that may otherwise negatively affect American economic interests." The investigation was conducted under the Section 301 of the Trade Act of 1974, and therefore is also referred to as a Section 301 investigation. After conducting a seven-month investigation, the USTR issued a report on March 22, 2018.[1] On the same date, Trump signed a presidential memorandum to announce that additional tariffs would be applied on Chinese products. On April 3, 2018, the USTR released a list of Chinese products to be levied with 25 percent additional tariffs. This list is often referred to as the *$50 billion list* in the media, since the US imports of these products from China in 2017 were worth 50 billion USD. On June 18, 2018, Trump directed the USTR to identify an additional $200 billion worth of Chinese goods for additional tariffs at a rate of 10 percent, which the USTR did in a list released on July 10, 2018 (known as the *$200 billion list*).

The details of the above tariffs (hereafter, Trump's China tariffs) were officially published as the two following documents in the website of the Federal Register (`www.federalregister.gov`):

- *Notice of Action and Request for Public Comment Concerning Proposed Determination of Action Pursuant to Section 301* (Docket Number USTR–2018–0018);
- *Request for Comments Concerning Proposed Modification of Action Pursuant to Section 301* (Docket Number USTR-2018-0026).

There is also an online summary in the website of the USTR that lists all documents related to Trump's China tariffs (see Appendix A.1).

[1] The report, titled *Findings of the Investigation into China's Acts, Policies, and Practices Related to Technology Transfer, Intellectual Property, and Innovation Under Section 301 of the Trade Act of 1974*, is publicly available at https://ustr.gov/sites/default/files/Section%20301%20FINAL.PDF. The instructions given by Trump to the USTR, as cited earlier in this paragraph, can also be found in the report (page 4).

In the first document above, an additional tariff of 25 percent was applied on 1,102 products. Products are defined using eight-digit HTSUS product codes in the document, the first six digits of which stem from the internationally used Harmonized System (HS) classification codes for traded goods. Tranche 1 in this document includes 818 products, as detailed in ANNEX B of the document. US imports of these products from China in 2017 were worth 34 billion USD. Tranche 2 includes 284 products, as detailed in ANNEX C of the document. The US imports of these products from China in 2017 were worth 16 billion USD. These two value estimates, 34 billion USD and 16 billion USD, constitute the $50 billion list mentioned above. In the second document, an additional tariff of 10 percent was applied on 6,031 products. This is Tranche 3, which corresponds to the $200 list mentioned above.

In the three tariff tranches, there are 7,133 eight-digit HTSUS product codes levied with additional tariffs. These tariffs were revised and put into effect in the following months. We converted the eight-digit HTSUS product codes to six-digit HS codes such that they can be matched with industry-level employment data. A six-digit product code is counted as a product levied with the additional tariff, if any eight-digit product code under it appears to be in the above tranches. This unification in coding is important for our empirical implementation. The 7,133 eight-digit products are aggregated into 3,838 six-digit products. Most of these products had been actively traded. In the year prior to the election (2017), 3,306 out of the 3,838 six-digit products were imported by the US from China. Not all US imports from China are levied with the additional tariffs. There are 1,283 six-digit products that were imported by the US from China in 2017 but do not appear to be in the above tranches.

The majority of the 3,838 six-digit product codes in the tariff tranches contain only a few eight-digit product codes. Specifically, 2,472 of the six-digit product codes have only one eight-digit product code listed under them, 686 of them have two listed under, 259 have three listed under, and 421 have more than three listed under. This highly skewed distribution, as reported in detail in Table A1, implies that using six-digit product codes to merge the products to industry-level employment does not cause significant information loss.

2.2 Election-related Data

Our election-related data were obtained from multiple sources, the details of which are provided in Appendix A.1. The house election results were purchased from *Dave Leip Atlas*, a company that collects data on US public office elections from official sources and compiles them into commercial databases. The original data report the total votes received by each party in every US county. We follow Autor et al. (2020) and Jensen et al. (2017) to construct the share of votes received by Republican house candidates out of the total votes received by the candidates of both parties. We refer to this variable as *Republican vote share*, denoted by $R_{c,t}$ for county c in year t, $t = 2016$ or 2018.

Every house representative in the US is elected by voters in a given congressional district. Congressional districts are apportioned among states based on population. There are 435 congressional districts in the US, each of which is assigned one house seat held by one representative who is elected for a two-year term. A congressional district can be comprised of multiple counties, one whole county, part of a county, or a collection of areas spanning multiple counties. Our sample includes 3,140 counties, 2,734 of which are located within one single congressional district. Following the literature, we choose counties as the unit of analysis because they are the smallest possible unit of local economy in the US economic statistics.[2] At the same time, since election outcomes depend on congressional district level voting results, congressional district level incumbencies should not be ignored. In fact, some of our findings pertain to district level incumbencies. To that end, we expand the sample to the county-district level when needed. Details of the county-district level sample will be provided when we discuss the corresponding results.

The data on manufacturing employment across counties were downloaded from the County Business Patterns (CBP) database maintained by the US Census Bureau. The latest data available for downloading are for the year 2016. The CBP data are published by the US Census Bureau at the county-industry level.[3] Our analysis also involves other county characteristics. Following Autor et al. (2020), Che et al. (2016), and Freund and Sidhu (2017), we include median income, unemployment rates, labor participation rates, manufacturing employment shares, education level, demographic characteristics, and religion. The demographic statistics were obtained from the American Community Survey (ACS). The religion-related data were obtained from the Association of Religion Data Archives (ARDA). Their details are provided in Appendix A.1.

2.3 Exposure to Trump's China Tariffs

To measure county-level exposure to Trump's China tariffs, we matched the tariffs to every county's manufacturing employment across its industries. The tariff rates were set at the product level, while manufacturing employment is available at the county-industry level. The incompatibility in their formats is resolved by our application of the method originated by Autor et al. (2013) and Acemoglu et al. (2016). Their method has been widely used in the literature to measure regional exposure to industrywide economic shocks, including Autor et al. (2020), Lu et al. (2018),

[2]See, for example, Lu et al. (2018), Che et al. (2016), Pierce and Schott (2020), Wright (2012), Kriner and Reeves (2012), Jensen et al. (2017), Freund and Sidhu (2017), and Blanchard et al. (2019). To examine the impact of economic shocks on aggregated economic behaviors (such as voting) in the US, the unit of analysis used in the literature is mostly either a county or a cluster of counties (such as a commuting zone). The data on economic fundamentals in nationally consistent formats are available at levels no lower than the county level. Either aggregating county level data to the congressional district level, or disaggregating county level data across its multiple congressional districts, would require making assumptions about the geographical distributions of voters within and across counties. The measurement of tariff exposure (our variable of interest, as described in the next subsection) would be directly driven by such assumptions if we use clusters of counties as the unit of analysis.

[3]CBP reports intervals rather than counts of employment for counties where specific employers could be identified in the data. For counties whose employment is reported as intervals, we follow Autor et al. (2013) to impute the employment (see their Online Appendix I.B for details).

and Pierce and Schott (2020). The idea behind their method is to measure the exposure to competing Chinese products in a US region by weighting the industrywide shock with the employment composition across industries within the region and then aggregating the weighted industrywide shocks to the region level. Our measure of the exposure to Trump's China tariffs is

$$TrumpTariffExpo_c = \sum_{p \in c} \frac{L_{c,j(p)}}{L_{j(p)}} \Delta t_p^{Trump}, \tag{1}$$

where Δt_p^{Trump} is the additional tariff levied on product p. Here $j(p)$ denotes a conversion of the Δt_p^{Trump} from the product p level to the industry j level through the product-industry concordance compiled by Pierce and Schott (2012).

The rationale underlying the product-based measure (1) is worth elaborating on. The ideal data for this study would allow us to know the products produced in every US county such that we can determine every county's exposure by counting their products listed in Trump's tariff tranches. Because such county-level product data do not exist, we construct the number of industries in each county related to the products shielded by Trump's tariffs from Chinese competition. Specifically, the weight $L_{c,j(p)}/L_{j(p)}$ in exposure measure (1) serves two purposes. First, it assigns product-level tariffs to counties through the industry composition of employment in each county. Second, it adjusts for the differing importance of distinct products (proxied for by industries) in a given county. For example, a county having 10 products levied with Trump's tariffs does not have 10 times larger tariff exposure than a county having one product levied with Trump's tariff. If the 10-products levied with Trump's tariffs account for little employment in the former county, where local employment concentrates on products not levied with the tariffs, the former county's tariff exposure would actually be smaller than a second county where local employment is all associated with the single product levied with Trump's tariff. This is an extreme example, but one which illustrates how the number of products exposed to Trump's tariffs should be weighted by employment.

A shortcoming of exposure measure (1) is that the weights do not add up to one within a given county. A county that happens to produce a large number of products that are listed in Trump's tariff tranches could have unbounded tariff exposure value. We also prepared an alternative measure of the exposure to Trump's China tariffs:

$$TrumpTariffExpo'_c = \sum_{j \in c} \frac{L_{c,j}}{L_j} \Delta t_{j(p)}^{Trump}. \tag{2}$$

where the weights automatically normalize employment (thus political voices) within a given county. The shortcoming of exposure measure (2) is that multiple products related to the same industry are treated by the exposure measure in the same way as one single product in the industry. Consider 50 products made in industry j. Given that industry j accounts for 10 percent of employment in county c, a county c that has one product in industry j levied with Trump's tariffs, according to exposure measure (2), has exactly the same tariff exposure as a county c in industry j that has 50 products levied. This is legitimate only if voters employed in industries exposed to Trump's tariffs care about whether their industries are affected or not as a whole rather than how their own jobs (usually related to specific products) are affected. We find the imposition of such voter perception to be restrictive. Moreover, Trump's tariffs across products are far sparser than import penetration across industries — most industries do not exist in most counties and such sparsity is more severe at the product level. With all these factors considered, we use exposure measure (1) in our main results and exposure measure (2) as a robustness check.

The upper panel of Figure 1 shows the geographical distribution of the tariff exposure constructed above. In addition to the variables described above, we constructed other measures of tariff exposure and an instrumental variable. The geographical distribution of the instrumental variable, displayed in the lower panel of Figure 1, will be detailed when we discuss the corresponding results. Table 1 reports the summary statistics of our working sample. We now move on to our empirical specification and findings.

3 Main Findings

3.1 OLS Results

We start with a baseline ordinary-least-squares (OLS) estimation following Autor et al. (2020):

$$R_{c,2018} - R_{c,2016} = \alpha_0 + \alpha_1 TrumpTariffExpo_c + \mathbf{X}_c\vec{\beta} + \gamma_{s(c)} + \varepsilon_c, \tag{3}$$

where the dependent variable is the change in the county (c)-level Republican vote share R_c between the house elections of 2018 and the house elections of 2016. $TrumpTariffExpo_c$ is the aforementioned tariff exposure measure and $\mathbf{X}_c$ is a vector of control variables. $\gamma_{s(c)}$ is a state fixed effect, where $s(c)$ denotes the state of county c. ε_c is the error term, which is clustered at the state level. The regression is weighted by the number of votes cast in the county at the midterm elections, in order to adjust the relative importance of counties in determining the election outcome (alternative weights will be used as a robustness check).

The results from regression specification (3) are reported in Table 2, showing that a greater tariff exposure is associated with stronger support for the Republican house candidate. We start with the full sample (column (1)), where a one standard deviation increase in the exposure is associated with a 24 percentage point increase in the Republican vote share (that is, $0.008 \times 30.4 = 0.24$). We next move on to the counties in states that voted for Republican presidential candidates between 1992 and 2016 (i.e., "red states" in column (2)), and then examine the counties in states

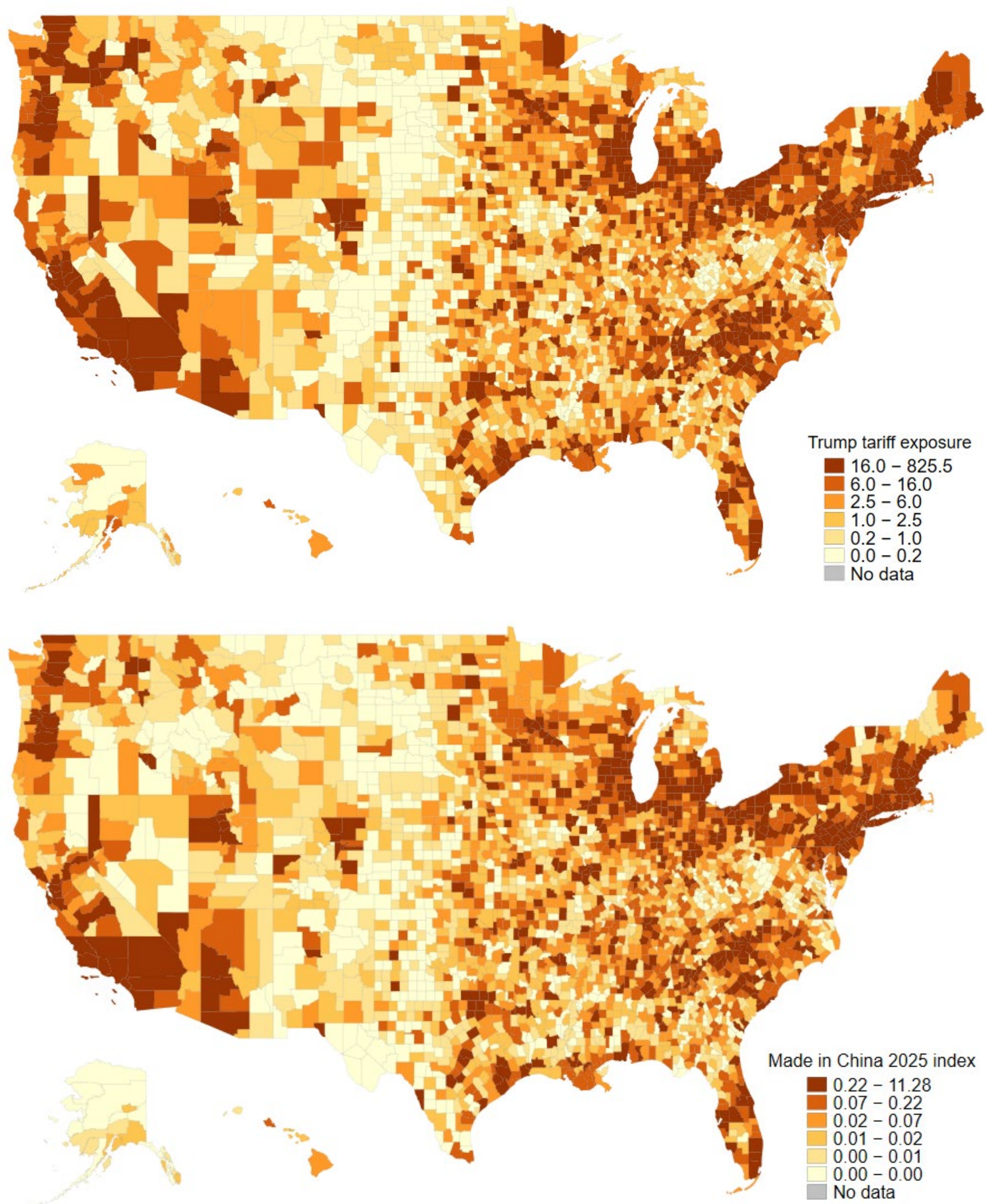

Figure 1:

Cross-county Exposure to Trump's China Tariffs and China's Made-in-China 2025 Initiative

The upper panel displays the value of our main explanatory variable (exposure to Trump's China tariffs; see Section 2.3 for details). The lower panel displays the value of our instrumental variable used in our 2SLS estimation (exposure to China's Made-in-China 2025 Initiative; see Section 3.2 for details).

Table 1: Summary Statisitcs

	(1) Obs.	(2) Mean	(3) S.D.	(4) Min	(5) Max
Panel A: Election-related variables†					
Republican vote share 2018	3140	0.617	0.189	0	1
Republican vote share 2016	3137	0.659	0.205	0	1
Panel B: Exposure to Trump's China tariffs					
Trump tariff exposure§	3140	10.709	30.417	0	825.479
Trump tariff exposure (without exemptions)◊	3140	10.402	29.525	0	795.615
Trump tariff exposure (binary)◊	3140	0.800	2.300	0	66.616
Trump tariff exposure, alternative measure§	3140	10.455	29.755	0	820.482
MIC2025¥	3140	0.166	0.535	0	11.279
Panel C: County characteristics£					
Manufacturing share (%)	3139	29.362	12.536	2.716	139.982
Median wage (log)	3139	10.783	0.251	9.866	11.772
Labor participation rate (%)	3139	58.662	8.032	11.600	84.400
Unemployment rate (%)	3139	6.358	3.036	0	28.700
Population (log)	3139	10.271	1.482	4.304	16.129
High school (%)	3139	33.398	7.572	6.695	56.571
College degree (%)	3139	32.772	5.679	8.527	50.510
Bachelor degree or higher (%)	3139	21.866	9.713	3.975	79.551
Black (%)	3139	7.104	11.332	0	69.207
Asian (%)	3139	1.083	2.287	0	37.618
Hispanic (%)	3139	6.325	9.942	0	70.528
Male (%)	3139	50.839	3.451	39.621	92.109
Age 16-29 (%)	3139	17.392	4.194	2.930	59.609
Age 30-54 (%)	3139	30.722	2.941	10.980	46.917
Age 55-74 (%)	3139	24.320	4.459	6.498	62.162
Protesetant adherents (%)	3090	74.310	23.779	0	100
Catholic adherents (%)	3090	20.443	20.036	0	100
Orthodox adherents (%)	3090	0.255	2.749	0	87.091

Each observation is a county. Panel A relates to dependent variables in our analysis, obtained from Dave Leip Atlas. Panel B relates to main explanatory variables (including instrumental variable MIC2025) in our analysis, which were constructed by authors using data from multiple sources. Panel C relates to control variables in our analysis, obtained from various sources.

† Defined in Section 2.2.
§ Defined in Section 2.3.
◊ Defined in Section 3.1.
¥ Defined in Section 3.2.
£ See Appendix A.1 for sources.

that voted for Democratic presidential candidates (i.e., "blue states" in column (3)) between 1992

Table 2: The OLS Results

	(1)	(2)	(3)	(4)	(5)
Dep. variable:	Difference in the Republican vote share (2018 minus 2016)				
Sample:	All	Red	Blue	Republican incumbent	Democratic incumbent
Trump tariff exposure	0.008*	0.005*	0.014***	0.005	0.010*
	(0.005)	(0.002)	(0.003)	(0.004)	(0.006)
Manufactering share	-0.021	-0.045	-0.042	-0.047	-0.055
	(0.025)	(0.044)	(0.039)	(0.032)	(0.039)
Median wage (log)	5.204	-7.472	-7.921	5.611	1.160
	(5.356)	(7.080)	(5.337)	(5.738)	(9.076)
Labor participation rate	-0.114	0.040	-0.010	-0.029	-0.181
	(0.105)	(0.146)	(0.284)	(0.137)	(0.201)
Unemployment rate	0.488**	-0.048	0.137	0.327	0.749
	(0.242)	(0.193)	(0.771)	(0.219)	(0.509)
Population (log)	-0.734	-1.556	-0.619	-0.783	-1.555
	(0.536)	(0.896)	(0.748)	(0.518)	(1.141)
Education-related dummies	Yes	Yes	Yes	Yes	Yes
Ethnicity-related dummies	Yes	Yes	Yes	Yes	Yes
Age-related dummies	Yes	Yes	Yes	Yes	Yes
Religion-related dummies	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	3087	953	477	2648	614
Adjusted R-squared	0.174	0.128	0.334	0.179	0.253

This table presents our baseline OLS results. Column (1) uses the full sample, where sample size 3,087 refers to all counties with nonmissing depndent and explanatory variables (including control variables). Columns (2) and (3) limit the sample to the counties located in red and blue states, respectively. Red and blue states were designated based on previous presidential election results (see Section 3.1 for details). Columns (4) and (5) limit the sample to the counties having incumbents all from one single party. Counties split across congressional districts are kept, and all their incumbents are considered (see Section 3.1 for details). The results with all such counties excluded are reported in Appendix A.2. Robust errors are clustered at the state level.* p<0.10, ** p<0.05, *** p<0.010.

and 2012.[4] The results in these two columns are similar to those in column (1), with the blue-state results being larger and more significant.[5]

We also run the regression for congressional districts with Republican and Democratic in-

[4]Since Donald Trump won several previously blue states in 2016, we do not use the 2016 presidential election results to designate blue states. Nonetheless, with those blue states designated as blue states, our main findings remain the same (available upon request).

[5]The subsample sizes in columns (2) and (3) do not add up to the sample size in column (1) because many states are neither red nor blue.

cumbents separately. Recall that the US house constituencies are congressional districts rather than counties. A county is a collection of partial or whole congressional districts, and therefore may have multiple house incumbents depending on the degree of its overlap with congressional districts. We could split a county into different sub-counties that each correspond to a unique congressional district. However, tariff exposure measure (2), constructed using employment data from the CBP database, cannot be disaggregated beyond the county level. To address the multiple incumbency issue, we create county-district duplets that each correspond to a unique congressional district. For example, if a county involves three congressional districts, it will show up in an expanded sample three times. Every time it appears in the expanded sample, it has the same county characteristics (including the tariff exposure) but is assigned a different congressional district incumbent. By expanding the data in this way, we maximize the use of county characteristics and incumbent affiliations, ending up with 3,262 county-district duplets (2,648 Republican duplets and 614 Democratic duplets). Notice that the merge of given counties with different incumbents tends to attenuate the relevance of county characteristics (including tariff exposure) to political proclivity.[6] Nonetheless, as shown in columns (4) and (5) of Table 2, the counties with a higher tariff exposure show more support for Republican candidates in places where the incumbents are Democrats, but not in places where the incumbents are Republicans.

As an alternative to expanding the sample, we experiment with decreasing the sample. The multiple incumbency issue can also be addressed by dropping all counties that correspond to incumbents from different parties. For example, if a county involves three congressional districts all having either Republican or Democratic incumbents, the county will be kept in the sample. However, if one of the three incumbents has a party affiliation different than the other two, the entire county will be dropped from the sample. The results from the decreased sample are similar, the details of which are discussed in Appendix A.2. The similarity is unsurprising because as mentioned earlier, the majority of US counties coincide with only one congressional district, and among those with more than one congressional district, the cases having opposing incumbents are fewer still. Since the counties in the decreased sample, if combined, would not include all constituencies of the US, we find this approach lacking in completeness and thus leave the discussion of this approach to the appendix.

We would like to make a technical note on the subsamples used in columns (2) to (5) in Table 2. Republicans controlled the house with a 235:193 majority (approximately 1.2 to 1) before the midterm, whereas the red/blue subsample size ratio in columns (2) and (3) is 953:477 (approximately 2.0 to 1) and the contrast rises to 2648:614 (approximately 4.3 to 1) in columns (4) and (5). These ratios vary considerably in magnitude, though they should not be compared at face value.

[6] Suppose that a given set of county characteristics are randomly assigned Republican and Democratic incumbents with equal probability. Then the county characteristics become party-neutral and thus independent from the incumbent-based subsample division in columns (4) and (5) of Table 2. As a result, the findings from the two columns should be the same.

First, the red/blue subsample division builds on presidential elections in previous decades, which have no direct relationship with the house election in 2018. Moreover, the division is made at the state level. That is, all counties in a red (blue) state are counted as red (blue) counties in column (2) (column (3)). Second, the incumbent-related columns (4) and (5) rest on the county-district level expanded sample. The Republican incumbencies are magnified in the sample by their relative advantage in rural areas. Since population density is lower in rural areas than in urban areas, the congressional districts in rural areas, which are apportioned according to population just like those in urban areas, span more counties than those in urban areas. These technicalities should be noted since the same column structure will be used again when we present the 2SLS results.

Table 3: Robustness Checks on the OLS Results

	(1)	(2)	(3)	(4)	(5)
Dep. Variable:	Difference in the Republican vote share (2018 minus 2016)				
Specification:§	Difference in differences◊	Without exempted products	Binary tariffs	Alternative exposure formula	Alternative weights
Trump tariff exposure	0.015***	0.008*	0.097	0.008*	0.008*
	(0.005)	(0.005)	(0.061)	(0.005)	(0.004)
Control variables†	Yes	Yes	Yes	Yes	Yes
County FE	Yes	No	No	No	No
State FE	No	Yes	Yes	Yes	Yes
Observations	6174	3087	3087	3087	3087
Adjusted R-squared	0.534	0.174	0.173	0.174	0.173

§ See the text (Section 3.1) for the details of each check (regression specifications are otherwise the same as in column (1) of Table 2). † Control variables are the same as in Table 2. ◊ Unlike other columns, which use the county level sample, column (1) uses a county-year level sample. Robust errors are clustered at the state level. * p<0.10, *** p<0.010.

In Table 3, we report five robustness checks on the findings from Table 2. First, we conduct a difference-in-differences regression

$$R_{c,t} = \delta_0 + \delta_1 TrumpTariffExpo_c \times \mathbb{I}(t = 2018) + \mathbf{X}_{c,t}\bar{\zeta} + \eta_c + \eta_t + \varepsilon_{c,t}, \tag{4}$$

where both the dependent and control variables are now time-variant (2016 and 2018). Here $\mathbb{I}(t = 2018)$ is a dummy variable that equals 1 if the observation is from the year 2018. $\mathbf{X}_{c,t}$ denotes county-year level control variables (if available). Given the county-year level variations in use, we can now include a county fixed effect η_c and a year fixed effect η_t, both of which are not usable in Table 2. Notice that both $TrumpTariffExpo_c$ and $\mathbb{I}(t = 2018)$ enter into the regression as an interaction term, and their variations are absorbed by the two fixed effects. Regression specification

(4) displays a similar correlation between tariff exposure and support for Republicans, as shown in column (1) of Table 3.

Columns (2) to (5) of Table 3 switch back to our original regression specification (3). In column (2), we exclude the products that were later exempted from the China tariffs. There exist a small number of products exempted from the lists of Tranches 2 and 3 when the two lists took effect.[7] In column (3), we replace the tariff differential Δt_p^{Trump} in exposure measure (1) with a binary variable $\mathbb{I}[\Delta t_p^{Trump} > 0]$. This change in the construction of the exposure measure dilutes its variation, because it uses only the variations along the extensive margin of the tariffs. The coefficient remains positive, though no longer statistically significant. In column (4), we use the aforementioned alternative exposure measure (2). In column (5), we use county-level population instead of voter number to weight the regression. These columns deliver results that resemble those in Table 2.

3.2 2SLS Results

The positive association between county-level tariff exposure and support for Republicans, as shown in Tables 2 and 3, does not necessarily imply a causal effect of the former on the latter. The Trump administration has an incentive to apply additional tariffs on Chinese products that compete with US products produced in counties with more pro-Republican voters. Many pro-Republican voters support Trump and blame China for job losses. The import penetration of Chinese products in the US and world markets, concentrated in relatively unskilled labor intensive products, potentially cause endogeneity in the OLS estimation. To address the potential endogeneity, we instrument the tariff exposure measure using the Chinese government's Made-in-China 2025 Initiative (hereafter, MIC2025). The initiative was released by the Chinese government in 2015 to guide domestic investments. It aims to develop domestic industrial capabilities in manufacturing high-technology products such as aircraft, robots, and new energy automobiles. We manually match the focal industries in the MIC2025 to four-digit product (HS) codes (see Appendix A.3 for details). MIC2025 directly motivated Trump's China tariffs, as made clear by the Trump administration when it launched the China tariffs:[8]

> *Under Section 301 of the Trade Act of 1974, the United States will impose a 25 percent tariff on $50 billion of goods imported from China containing industrially significant technology, including those related to the "Made in China 2025" program.*

This motivation for Trump's China tariffs was also articulated in the USTR announcement of the first-round tariffs (see the first document listed in Section 2.1).

Our identification assumption is that MIC2025 has no impact on US house election results at

[7] Five (out of 284) products are exempted from Tranche 2, and 297 (out of 6,031) products from Tranche 3. See Appendix A.1 for details. All the products mentioned here refer to eight-digit product (HTSUS) codes.

[8] See *Statement on Steps to Protect Domestic Technology and Intellectual Property from China's Discriminatory and Burdensome Trade Practices* (May 29, 2018). The statement is downloadable at `www.whitehouse.gov/briefings-statements/`.

the county level except through Trump's China tariffs. We consider this assumption to be quite reasonable, since MIC2025 is an expression of intent without implementable details. Aiming at products that do not match China's current industrial capacities, the initiative is a long shot that has yet to be developed by the Chinese government into industrial or trade policies. In fact, as an identification check, we examine the exports and imports of the US between 2005 and 2018 and find no different trend in its trade volume of MIC2025-related products before and after the release of MIC2025 by the Chinese government (see Section 4.3). Trump's China tariffs are a precautionary measure designed to deter China's aggression by reducing its production capacity, R&D resources, and intellectual property maneuvers. In other words, the threats posed by Chinese competition on the US production and employment come from products currently made in China rather than products to be made in China in 2025.

Take the product "pneumatic tires on aircraft" at the top of the Tranche 1 list for example. Its presence in Trump's China tariffs is not because China has an aircraft industry that can compete with the US — China does not — but rather because such a tariff will curtail China's ability to build such an aircraft industry in the future. The tariff on aircraft tires made in China does shield US aircraft tire makers from Chinese competition and benefit workers in the US industry, but that is an effect on the Republican vote share through the tariff rather than bypassing the tariff, thereby not failing the exclusion condition of our instrumental strategy.

We construct the instrumental variable at the county level by aggregating US products mentioned in MIC2025 to the county level:

$$MIC2025_c = \sum_{p \in c} \frac{L_{c,j(p)}}{L_{j(p)}} MIC2025_p, \tag{5}$$

where $MIC2025_p$ is the four-digit product (HS) code that we identified from the official MIC2025 document. Similar to $TrumpTariffExpo_c$, $MIC2025_c$ as an aggregate across products is not bounded from above. The geographical distribution of $MIC2025_c$ is demonstrated in the lower panel of Figure 1, which resembles the geographical distribution of the tariff exposure in the upper panel of the figure.

Before using $MIC2025_c$ for the 2SLS estimation, we conduct a regression analysis that uses $MIC2025_p$ to explain Trump's China tariffs lists. The results are reported in Table 4, where the dependent variable is either an indicator variable that equals 1 if the associated Chinese product is levied with Trump's China tariffs, or the effective full tariff rate (i.e., with Trump's additional tariffs included) applied on the associated Chinese product. In Panel A, each observation relates to one four-digit product (HS) code. Our $MIC2025_c$, as noted above, is constructed at the four-digit product code level. Here, the China tariffs indicator is equal to 1 if any six-digit product under the four-digit product code is levied with the new tariffs. In Panel B, each observation is a six-digit product code, and our $MIC2025_p$ remains at the four-digit level. Our use of different levels of aggregation aims to avoid aggregation-induced spurious correlation. We include two-digit product fixed effects in all regressions. In addition, we experiment with excluding the products later exempted from China tariffs. Overall, as shown in Table 4, there is a strong association between Trump's China tariff lists and China's MIC2025 product lists. Quantitatively, within each two-digit product code, being listed in China's MIC2025 raises the probability of having Trump's China tariffs applied by 10 to 18 percent and raises the tariff rate by 2.2 to 3.7 percentage points.

Table 4: Correlation between MIC2025 and Trump's China Tariffs at the Product Level

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable:	Applied Trump's China tariffs		New tariff rate	Applied Trump's China tariffs (without exemptions)		New tariff rate (without exemptions)
	Indicator **I** (=1 if applied)		(Percentage points)	Indicator **I** (=1 if applied & effective)		(Percentage points)
Estimation:	Linear	Probit	Linear	Linear	Probit	Linear
Panel A: Each product is a four-digit HS product code						
MIC2025	0.099***	0.177**	3.248***	0.102***	0.178**	3.525***
	(0.036)	(0.081)	(0.902)	(0.036)	(0.082)	(0.841)
Two-digit HS FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,160	1,160	1,160	1,130	1,130	1,130
R-squared	0.629	n/a	0.634	0.626	n/a	0.633
Panel B: Each product is a six-digit HS product code						
MIC2025	0.115***	0.117**	3.644***	0.112***	0.112**	3.732***
	(0.042)	(0.045)	(0.796)	(0.041)	(0.043)	(0.772)
Two-digit HS FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,589	4,589	4,589	4,483	4,483	4,483
R-squared	0.538	n/a	0.503	0.536	n/a	0.510

This table presents the correlation between MIC2025 and Trump's China tariffs at the product level. Each product refers to a four (six) digit HS product code in Panel A (Panel B). Within columns (1) to (3), columns (1) and (2) use an indicator variable (equal to 1 if Trump's China tariffs are applied on any of the products under the four or six digit product code) as the dependent variable, and column (3) uses the average tariff rates with Trump's China tariffs included as the dependent variable. Column (1) uses a linear probability model, column (2) uses a probit model, and column (3) uses a regular linear regression. The same three-column structure applies to columns (4)-(6), where exempted products are excluded. Marginal effects are reported for probit models (standard errors estimated using the delta method). Robust standard errors in parentheses, clustered at the two-digit HS product code level. *** p<0.01, ** p<0.05.

By instrumenting the tariff exposure with $MIC2025_c$, we conduct 2SLS estimation and report the results in Table 5. As indicated in column (1), a further exposure to Trump's China tariffs raises local support for Republican house candidates. The size of the coefficient 0.010 is close

Table 5: The 2SLS Results

	(1)	(2)	(3)	(4)	(5)
Sample	All	Red	Blue	Republican incumbent	Democratic incumbent
Panel A: The second stage					
Dep. variable is differenced republican vote share					
Trump tariff exposure	0.010**	0.003	0.019***	0.006	0.013*
	(0.005)	(0.003)	(0.005)	(0.004)	(0.007)
Control variables†	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	3087	953	477	2648	614
Adjusted R-squared	0.056	0.099	0.181	0.065	0.117
Panel B: The first stage					
Dep. variable is Trump tariff exposure					
MIC2025	55.815***	100.316***	44.428***	62.343***	54.678***
	(7.982)	(7.641)	(2.200)	(8.913)	(9.533)
F-statistics	48.89	172.36	407.99	48.92	32.9

This table presents our baseline 2SLS results. Column (1) uses the full sample, where the sample size 3,087 refers to all counties with nonmissing depndent and explanatory variables (including control variables). Columns (2) and (3) limit the sample to the counties located in red and blue states, respectively. Red and blue states were designated based on previous presidential election results (see Section 3.1 for details). Columns (4) and (5) limit the sample to the counties having incumbents all from one single party. Counties split across congressional districts are kept, and all their incumbents are considered (see Section 3.1 for details). The results with all such counties excluded are reported in Appendix A.2. † Control variables are the same as in Table 2. Robust errors are clustered at the state level.* $p<0.10$, ** $p<0.05$, *** $p<0.010$.

to its OLS counterpart (0.008) in Table 2. The two coefficients are within one standard error of each other. Also similar to the OLS findings, the results from relatively pro-Democratic counties (columns (3) and (5)) are stronger than those from relatively pro-Republican counties (columns (2) and (4)).[9] In fact, the coefficient in column (2) loses the statistical significance that it has in column (2), Table 2. The coefficient in column (4) is statistically insignificant in both Table 5 and Table 2. It is unsurprising that Trump's China tariffs did not generate further support for Republicans. The previous local support for Republicans (in 2016 and earlier) is likely to be a decision made by local voters with the expectation that the elected Republican administration and legislature would take a tough stance on China. Trump's China tariffs conform to their expectation and their reaction was already absorbed by the success of Republicans in the house elections of 2016.

The 2SLS results are only slightly different from the OLS results. Our interpretation of the slight differences is as follows. The association between having large tariff exposure and support-

[9]Similar to the OLS results, we also run the regressions using a decreased sample that excludes counties that have incumbents from different parties. The results, which turn out to be highly similar, are discussed in Appendix A.2.

ing Republicans is overestimated by OLS in Republican-leaning places because their voters expected Trump to take a tough stance on China, but is underestimated in Democrat-leaning places because their voters did not expect the tough stance on China taken by Trump who, in addition to being a Republican president, had family business in China and did not express a hawkish view on China during his campaign. This interpretation receives support from the opposite patterns in columns (2) to (5) of the two tables. Specifically, moving from OLS to 2SLS, the Republican-leaning places (columns (2) and (4)) lose statistical significance while the Democrat-leaning places (columns (3) and (5)) gain in both statistical significance and coefficient magnitude. The net of the two patterns produces a slight elevation in statistical significance and coefficient magnitude in column (1), Table 5 relative to column (1), Table 2.

Table 6: Robustness Checks on the 2SLS Results

	(1)	(2)	(3)	(4)
Specification:§	Without exempted products	Binary tariffs	Alternative exposure formula	Alternative weights
Panel A: The second stage				
Dep. variable is differenced Republican vote share				
Trump tariff exposure	0.010**	0.136**	0.010**	0.011**
	(0.005)	(0.067)	(0.005)	(0.005)
Control variables†	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	3087	3087	3087	3087
Adjusted R-squared	0.056	0.054	0.055	0.051
Panel B: The first stage				
Dep. variable is Trump tariff exposure				
MIC2025	54.368***	4.076***	54.639***	57.775***
	(7.55)	(0.728)	(8.075)	(9.051)
F-statistics	51.86	31.33	45.78	40.74

§ See the text (Section 3.2) for the details of each check (regressions are otherwise the same as in column (1) of Table 5). † Control variables are the same as in Table 2. Robust errors are clustered at the state level. ** p<0.05, *** p<0.010.

Following the structure of Table 3 (OLS robustness), we conduct robustness checks on the 2SLS estimation and report them in Table 6. Table 6 does not have a counterpart of the difference-in-differences specification (column (1) of Table 3) because our instrumental variable is cross-sectional. The rest of the robustness checks in Table 3 all have 2SLS counterparts in Table 6. The 2SLS results turn out to be quite robust. In particular, the tariff exposure constructed using binary tariff indicators, which is insignificant in column (3) of Table 3, is significant here. Its coefficient

0.136 indicates that a one standard deviation larger tariff exposure generates 31 more percentage points in the Republican vote share (that is, $0.136 \times 2.3 = 0.31$), which is quite close to that estimated by the baseline 2SLS results ($0.010 \times 30.4 = 0.30$).

4 Competing Explanations

In this section, we discuss four competing explanations for the results presented in Section 3: (1) Trump's H-1B and tax reforms, (2) China's retaliatory tariffs, (3) endogenous Made-in-China 2025 Initiative, and (4) pre-trends in American politics.

4.1 Trump's H-1B and Tax Reforms

In this subsection, we examine whether two other primary policy changes made by the Trump administration could explain the Republican midterm performance. Trump is an open critic of the H-1B visa program that grants foreigners permission to work in the US. Trump claims that the program replaces domestic workers with immigrants. He signed an executive order on April 18, 2017 that urges stricter and more selective H-1B visa approval in order to "ensure that H-1B visas are awarded to the most-skilled or highest-paid petition beneficiaries."[10] Although formal policy changes to the program were not made by the US Citizenship and Immigration Services (USCIS) until January 2019, an increase in denial rates and audit requests ("Requests for Evidence") came through in the year 2018. The denial rate for H-1B petitions rose to 15% in Fiscal Year 2018, up from 7% in Fiscal Year 2017.[11] Meanwhile, Trump, who had advocated for corporate tax cuts during his campaign, signed the Tax Cuts and Jobs Act (TCJA) in December 2017.[12] The TCJA was introduced by Republicans and passed largely along party lines in both chambers of Congress. Effective January 1, 2018, the TCJA lowered the corporate tax rate from 35% to 21%, and reduced or removed certain business-related tax deductions and credits at the same time.

We collected data on both policy changes to ascertain whether our previous results can be explained by these two contemporaneous policy changes.[13] The H-1B (visa) approvals for each sector (two-digit NAICS code) can be downloaded from the USCIS website. We calculated the 2018-minus-2017 difference in the number of H-1B approvals to measure the H-1B policy change. Since H-1B applications and approvals are based on fiscal years (which run October 1 through September 30), the 2018 H-1B approvals had all been completed by the time of the midterm elections. As shown in Figure 2, the number of approvals declined significantly in 2018, affecting Sector 54 ("Professional, Scientific, and Technical Services") the most. The approvals in some tra-

[10] The text of the executive order is available at https://www.whitehouse.gov/presidential-actions/presidential-executive-order-buy-american-hire-american/.

[11] See Table 7 in USCIS (2018).

[12] See Nunns et al. (2016) for an analysis of Trump's tax proposals during his presidential campaign.

[13] See Appendix A.1 for data details.

ditional businesses such as manufacturing and finance and insurance rose slightly but remained far from offsetting the overall decline. For corporate taxes, we use the effective tax savings (ETRs) estimated by the Penn Wharton Budget Model (PWBM). The PWBM estimated ETRs for each industry (two-digit NAICS codes) under both pre-TCJA and TCJA tax codes. As shown in Figure 2, the tax savings due to the TCJA are unsurprisingly concentrated in the manufacturing sector and the finance and insurance sector.

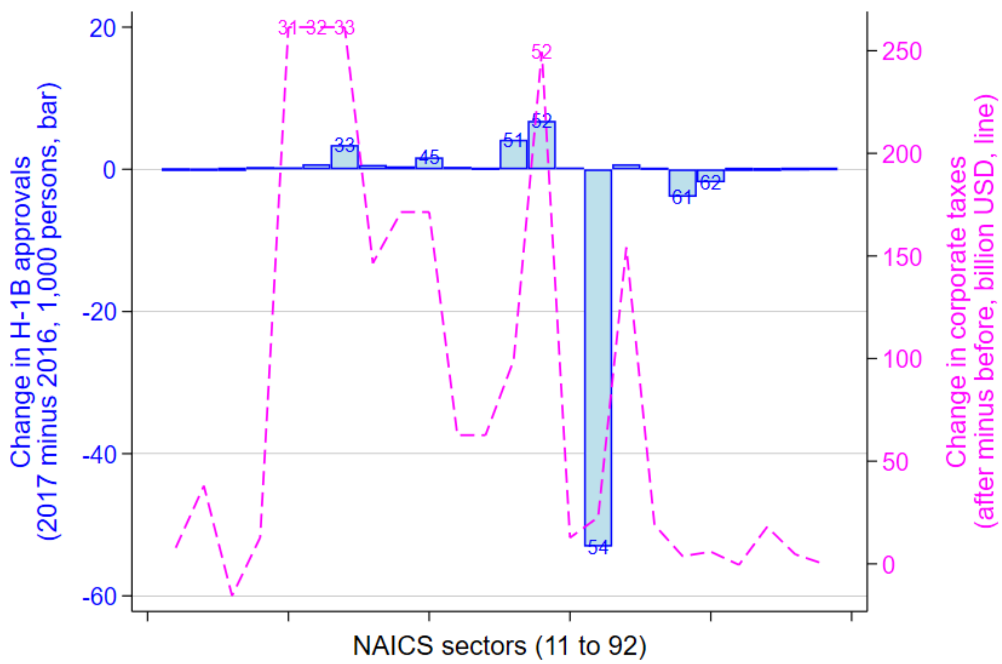

Figure 2:

Trump's Policy Changes Related to H-1B Visas and Corporate Taxes

Each NAICS sector refers to a two-digit NAICS code (ranging between 11 and 92). The bars represent 2017-minus-2016 differences in the number of H-1B approvals. The line represents after TJCA-minus-before TJCA differences in corporate tax payments. Sectors with large changes are marked in the chart, including:

31-33: Manufacturing
45: Retail Trade (including electronic shopping)
51: Information
52: Finance and Insurance
54: Professional, Scientific, and Technical Services
61: Educational Services
62: Health Care and Social Assistance

By merging the NAICS sectors with product (HS) codes, we categorize products into "high" and "low" groups for both policy changes. Specifically, the H-1B high (H-1B low) group refers to the products made in sectors with large (small) H-1B approval changes, while the tax-saving high (tax-saving low) group refers to the products made in sectors that are associated with large (small) tax savings due to the TCJA. By keeping only one out of the four groups of products in the sample, we recalculate tariff exposure measure (1). Each of the four resulting exposure measures considers only the China-tariff exposure influenced by one policy to one direction. For example, the empirical results associated with the H-1B high group are concerned with the China-tariff exposure without products made in sectors having fewer or no H-1B approval reductions. Similarly, the empirical results associated with the tax-saving high group pertain to the China-tariff exposure without products made in sectors with small, zero, or negative tax savings.

Our results, including OLS and 2SLS results, are reported in Tables 7 and 8. As before, we find stronger effects of the China-tariff exposure on the Republican vote shares in blue states than in red states. The only exception is the OLS result for the H-1B low group, where the positive association between high tariff exposure and strong support for Republicans applies only to red states (the second panel in Table 7). As explained in Section 3.2, we posit that the OLS-estimated correlation is upward (downward) biased in Republican-leaning (Democrat-leaning) places. Foreign workers as H-1B visa holders are hired less often in Republican-leaning , so that the OLS-estimated correlation tends to be upward biased. The positive association in red states disappears when 2SLS estimation is used (the fourth panel in Table 7).

We also experiment with reconstructing $MIC2025_c$ using products associated with different H-1B and tax policy changes. In this experiment, not only tariff exposure (1) but also instrument variable (5) depends on the policy change group in question. Take the H-1B high group, for example. The products listed in China's MIC2025 document, if produced in a sector with low H-1B approval changes, are excluded from the construction of $MIC2025_c$. The results from all the four policy change groups are reported in Tables A3 and A4, which highly resemble those reported in Tables 7 and 8. Since reconstructing both instrument and tariff exposure may cause a mechanical correlation between the two variables, this experiment serves only as a robustness check and we leave it to the appendix.

4.2 China's Retaliatory Tariffs

In response to each of the three tranches of Trump's China tariffs, the Ministry of Commerce of China announced a retaliatory tariff list. The three retaliatory tariff lists took effect, respectively, on July 6, August 23, and September 24 in the year 2018. The retaliation potentially influenced US midterm house elections. However, it is important to distinguish the influence of the retaliation on the midterm elections from the influence of the retaliation on *the impact of Trump's China tariffs on* the midterm elections. The latter is our research interest and has been captured by the coefficient of

Table 7: Competing Explanation IA — H-1B Policy Change

	(1)	(2)	(3)	(4)	(5)
Dep. variable:	Difference in the Republican vote share (2018 minus 2016)				
Sample:	All	Red	Blue	Republican incumbent	Democratic incumbent
	OLS Results — H-1B high group				
Trump tariff exposure	0.014**	0.009	0.022***	0.010*	0.018*
	(0.007)	(0.005)	(0.005)	(0.006)	(0.009)
Observations	3087	953	477	2648	614
Adjusted R-squared	0.175	0.128	0.338	0.180	0.255
	OLS Results — H-1B low group				
Trump tariff exposure	0.015	0.009*	0.023	0.009	0.019
	(0.011)	(0.005)	(0.016)	(0.009)	(0.013)
Observations	3087	953	477	2648	614
Adjusted R-squared	0.172	0.128	0.326	0.178	0.249
	2SLS Results — H-1B high group				
Second stage:					
Trump tariff exposure	0.015**	0.006	0.026***	0.010*	0.020**
	(0.007)	(0.007)	(0.006)	(0.006)	(0.010)
Observations	3087	953	477	2648	614
Adjusted R-squared	0.057	0.099	0.188	0.066	0.120
First stage:					
MIC2025	37.318***	53.020***	32.309***	40.121***	36.936***
	(3.185)	(3.291)	(1.073)	(3.302)	(3.942)
	2SLS Results — H-1B low group				
Second stage:					
Trump tariff exposure	0.030*	0.007	0.069***	0.018	0.042
	(0.016)	(0.007)	(0.019)	(0.012)	(0.026)
Observations	3087	953	477	2648	614
Adjusted R-squared	0.049	0.099	0.145	0.061	0.099
First stage:					
MIC2025	18.498***	47.297***	12.119***	22.222***	17.742***
	(4.837)	(4.356)	(1.400)	(5.652)	(5.644)

This table presents the identification check in Section 4.1. Column (1) uses the full sample. Columns (2) and (3) limit the sample to the counties located in red and blue states, respectively. Red and blue states were designated based on previous presidential election results (see Section 3.1 for details). Columns (4) and (5) limit the sample to the counties having incumbents all from one single party. Counties split across congressional districts are kept, and all their incumbents are considered (see Section 3.1 for details). Control variables (the same as in Table 2) and state fixed effects are included. Robust errors are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.010.

Table 8: Competing Explanation IB — Corproate Tax Savings

	(1)	(2)	(3)	(4)	(5)
Dep. variable:	Difference in the Republican vote share (2018 minus 2016)				
Sample:	All	Red	Blue	Republican incumbent	Democratic incumbent
OLS Results — Tax saving high group					
Trump tariff exposure	0.012	0.007*	0.028***	0.008	0.014
	(0.009)	(0.003)	(0.009)	(0.007)	(0.010)
Observations	3087	953	477	2648	614
Adjusted R-squared	0.173	0.129	0.333	0.178	0.249
OLS Results — Tax saving low group					
Trump tariff exposure	0.017**	0.013	0.024***	0.013*	0.024**
	(0.007)	(0.010)	(0.005)	(0.007)	(0.011)
Observations	3087	953	477	2648	614
Adjusted R-squared	0.174	0.127	0.334	0.180	0.256
2SLS Results — Tax saving high group					
Second stage:					
Trump tariff exposure	0.020*	0.005	0.045***	0.012	0.027
	(0.011)	(0.005)	(0.012)	(0.009)	(0.017)
Observations	3087	953	477	2648	614
Adjusted R-squared	0.052	0.099	0.177	0.063	0.104
First stage:					
MIC2025	27.267***	67.073***	18.395***	31.839***	26.898***
	(7.150)	(6.163)	(1.506)	(8.305)	(8.051)
2SLS Results — Tax saving low group					
Second stage:					
Trump tariff exposure	0.019**	0.010	0.032***	0.013*	0.027**
	(0.008)	(0.011)	(0.008)	(0.007)	(0.012)
Observations	3087	953	477	2648	614
Adjusted R-squared	0.056	0.098	0.181	0.066	0.121
First stage:					
MIC2025	28.549***	33.244***	26.033***	30.504***	27.780***
	(0.928)	(1.491)	(0.768)	(0.878)	(1.528)

This table presents the identification check in Section 4.1. Column (1) uses the full sample. Columns (2) and (3) limit the sample to the counties located in red and blue states, respectively. Red and blue states were designated based on previous presidential election results (see Section 3.1 for details). Columns (4) and (5) limit the sample to the counties having incumbents all from one single party. Counties split across congressional districts are kept, and all their incumbents are considered (see Section 3.1 for details). Control variables (the same as in Table 2) and state fixed effects are included. Robust errors are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.010.

$TrumpTariffExpo_c$ in our earlier results. Conceptually, our benchmark specification (3) identifies the sum of two effects:[14]

$$\underbrace{\left(\frac{\partial[R_{c,2018} - R_{c,2016}]}{\partial TrumpTariffExpo_c}\right)}_{\hat{\alpha}_1^{OLS} \text{ and } \hat{\alpha}_1^{2SLS}} = \text{direct effect}_c + \text{indirect effect}_c \tag{6}$$

$$= \text{direct effect}_c + \sum_{p' \in c} \underbrace{\frac{\partial \Delta R_c}{\partial \Delta t_{p'}^{China}}}_{\substack{\text{political feedback} \\ \text{to China's retaliation}}} \underbrace{\left(\sum_{p \in US} \frac{\partial \Delta t_{p'}^{China}}{\partial \Delta t_p^{Trump}}\right)}_{\substack{\text{China's retaliation} \\ \text{function}}}. \tag{7}$$

Equation (7) explicates the relations across three concepts. (i) Our research interest, in the form of $\hat{\alpha}_1^{OLS}$ and $\hat{\alpha}_1^{2SLS}$, is an estimated net effect of Trump's China tariffs on the midterm outcome for Republicans. (ii) "China's retaliation function" is a response function depending on the Chinese government's economic and political considerations. Specifically, in response to Trump's additional tariff on the Chinese product p (i.e., Δt_p^{Trump}), China retaliated by charging an additional tariff $\Delta t_{p'}^{China}$ on the US product p'. (iii) "Political feedback to China's retaliation" is the political responses of local voters to the Republican Party, given China's retaliation tariff on the US product p'. The aggregate response of the county is a summation across all products made in the county $\{p' \in c\}$. The voters who benefited from Trump's tariffs on Chinese products tend to support Trump's party (i.e., the direct effect), while those who were harmed by China's retaliation tariffs tend to blame and thus vote against Trump's party (i.e., the indirect effect). The relative strengths of the two forces are ambiguous, such that the total effect, as the net of the direct effect and the indirect effect, could be either positive or negative in theory.

As conceptually illustrated by equation (7), our previous estimation has accounted for the political feedback of voters when they are affected by Trump's tariffs indirectly through China's retaliation. The previously estimated $\hat{\alpha}_1^{OLS}$ and $\hat{\alpha}_1^{2SLS}$ reflect not just the direct effect in equation (7). They reflect a net effect of exposure to Trump's China tariffs, which is smaller than the direct effect because the indirect effect is potentially negative. Our previous results, showing political gains for Republicans from Trump's China tariffs, suggest that the negative indirect effect is insufficient to offset the positive direct effect. Since China's retaliation does not undermine our identification of the net effect, we need not separate the direct effect from the indirect effect. For that reason, we do not seek the separation in our previous results.

It might be tempting to construct county-level exposure to China's retaliation across counties and control for it in the same regression. That is, we could construct

$$ChinaRetalExpo_c = \sum_{p' \in c} \frac{L_{c,j(p')}}{L_{j(p')}} \Delta t_{p'}^{China}, \tag{8}$$

[14] See Appendix A.4 for derivation.

and add it to regression specification (3). However, this would cause several econometric problems. First and foremost, it would generate multicollinearity. There are three channels of the multicollinearity. (i) As explained above, the political feedback to China's retaliation has been an implicit part of the estimated $\hat{\alpha}_1^{OLS}$ and $\hat{\alpha}_1^{2SLS}$. (ii) The industrial composition term $\frac{L_{c,j(p)}}{L_{j(p)}}$ appears in the construction of both $TrumpTariffExpo_c$ and $ChinaRetalExpo_c$. (iii) Chinese imports and US imports have a large overlap, owing to the intensive outsourcing activities between the two countries.[15] Products outsourced by US firms to their Chinese subsidiaries and contractors are usually listed under the same product codes. Therefore, a large volume of imports by the US from China is usually accompanied by a large volume of imports by China from the US. The additional tariffs imposed by the two countries are positively correlated and thus cause multicollinearity. The outsourcing-induced multicollinearity hides in the summation operator in both exposure measures (1) and (8). Apart from multicollinearity, the correlation between $TrumpTariffExpo_c$ and $ChinaRetalExpo_c$ would render the endogeneity unsolvable when they are both included in the regression, since we do not have two distinct instruments for them.

Estimating the direct and indirect effects separately is tremendously challenging. Below, we propose a way to remove the indirect effect from the estimation. For each county c, we drop all its products that are included in China's retaliatory tariff lists. That is, we set the collection $\{p' \in c\}$ in equation (7) to be empty. As a result, the local political feedback in this simplistic conceptual framework is turned off — China's retaliation becomes irrelevant to the county c in focus — and the net effect then equals the direct effect. Put differently, with the retaliation-related products removed, $TrumpTariffExpo_c$ becomes conceptually retaliation-free such that its coefficient captures only the direct effect.

To illustrate the overlap between Trump's China tariffs and China's retaliation tariffs, we draw a heatmap at the four-digit product code level. Recall that our tariff exposure measures were constructed at the six-digit product code level. In the upper panel of Figure 3, each cell corresponds to a four-digit product code (the first two digits labeled in the horizontal axis, and the last two digits labeled in the vertical axis). Within each four-digit product code, the six-digit product codes levied with Trump's China tariffs are counted and assigned a heat level according to the count (light yellow for 0 and black for the maximum count). A grid of heat is displayed in the upper panel, with the background color set to the heat level of having no new tariff.[16] Using the upper panel as the benchmark, we subtract the counts of corresponding retaliation tariffs from the counts and display the net counts in the lower panel of the figure.[17] The removal

[15] According to Sposi and Koech (2013), the bilateral trade imbalance between the two countries would decrease by 33 percent if trade is calculated on a value-added basis to remove the double-counting caused by outsourcing.

[16] A cell with the background color represents three possibilities: (1) the cell does not correspond to any four-digit product code currently in use; (2) the US did not import products under the four-digit product code from China; (3) the Trump administration did not levy additional tariffs on the products under the four-digit product code imported from China.

[17] We downloaded China's retaliation tariff lists from the website of the Ministry of Finance of China (see Appendix

of the China retaliation tariffs remarkably reduces the overall heat levels. This indicates a heavy overlap between the export varieties and thus the tariff lists of the two countries, reflecting the intensive outsourcing activities between them mentioned earlier.

We then move on to the regression analysis. We conduct both OLS and 2SLS estimation as before, but replace the previous tariff exposure measure with its retaliation-free version described above. The results are reported in Table 9. Our previous results remain. Specifically, counties exposed more to Trump's China tariffs show stronger support for Republican candidates. This effect is particularly strong in the counties of congressional districts with Democratic incumbents. In addition, both the OLS- and 2SLS-coefficients are larger in magnitude than their counterparts in Tables 2 and 5. This suggests a negative indirect effect, which is in line with our expectation noted earlier. In other words, China's retaliation reduces local support for the Republicans, an effect that is implicitly present in Tables 2 and 5 but not in Table 9. In particular, notice that the coefficient of the exposure corresponding to the counties of congressional districts with Republican incumbents (column (4) in Panel B of Table 9) now turns significant at the 10% level, further pointing to a negative indirect effect through which some Republican-leaning voters who were negatively impacted by China's retaliation became less supportive of their Republican house candidates.[18]

4.3 Endogenous Made-in-China 2025

A potential concern over our previous instrumental strategy is that the Chinese government's Made-in-China 2025 Initiative (MIC2025), despite being a proposal without implementable industrial and trade policies, had *somehow* affected American voters by the time of the midterm elections. To look into this potential concern, we merged our MIC2025 product list with the product-level trade data of the US. The trade data used here cover a 14-year period, from the year 2005 to the midterm-election year 2018.[19] If MIC2025 influenced American voters through channels other than Trump's China tariffs, we should be able to detect the influences in the US trade statistics during this period, especially in the few years immediately preceding the 2018 house elections.

The two left-side panels of Figure 4 plots US imports from the rest of the world (top) and US exports to the rest of the world over time (bottom). In the figure, the dashed lines connected by solid circles correspond to the products related to MIC2025. The MIC2025-related products consumed and produced by the US appear to be quite stable in the few years around 2015 (the year when MIC2025 was released by the Chinese government). The stability is particularly salient when the dashed lines are compared against the more volatile solid lines connected by hollow circles that represent either total imports or total exports of the US. Then we examine US trade

A.1 for details).

[18] Our approach to addressing the indirect effect in equation (7) is to remove it rather than estimate it. The indirect effect remains to exist for those removed products.

[19] The Multifiber Arrangement (MFA) and its successor, the Agreement on Textile and Clothing (ATC), ended in 2005. This change had substantial impacts on Chinese exporters (see Khandelwal et al. (2013)).

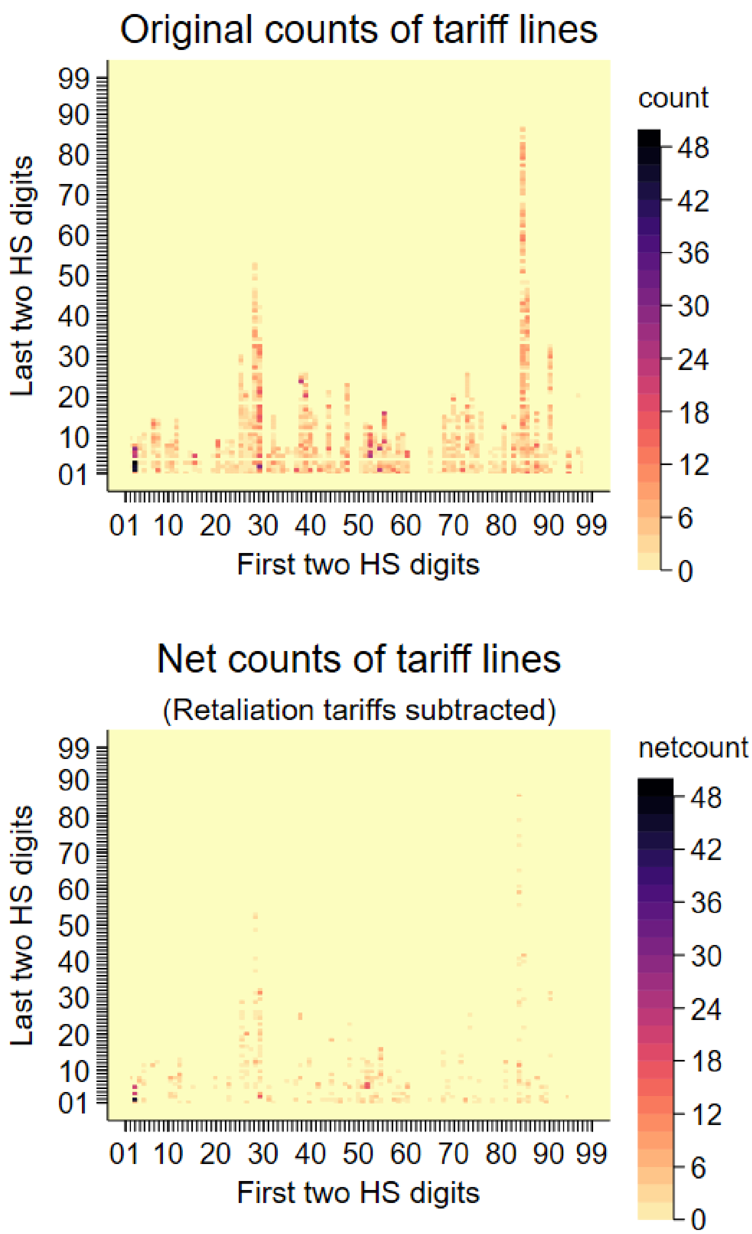

Figure 3: Trump's China Tariffs and China's Retaliation Tariffs

In both panels, each cell corresponds to a four-digit HS code (the first two digits labeled in the horizontal axis, and the last two digits labeled in the vertical axis). Within each four-digit HS code, the six-digit HS codes levied with Trump's China tariffs are counted and assigned a heat level according to the count (light yellow for 0 and black for the maximum count). A grid of heat is displayed in the upper panel, with the background color set to the heat level of having no new tariff. Using the upper panel as the benchmark, we subtract the counts of corresponding retaliation tariffs from the counts and display the net counts in the lower panel of the figure.

Table 9: Competing Explanation II — China Retaliation

	(1)	(2)	(3)	(4)	(5)
Dep. variable:	Difference in the Republican vote share (2018 minus 2016)				
Sample:	All	Red	Blue	Republican incumbent	Democratic incumbent
Panel A: OLS Results					
Trump tariff exposure	0.067***	0.042	0.041	0.057**	0.080**
	(0.024)	(0.038)	(0.026)	(0.023)	(0.036)
Control variables†	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	3087	953	477	2648	614
Adjusted R-squared	0.176	0.127	0.323	0.183	0.255
Panel B: 2SLS Results					
Second stage:					
Trump tariff exposure	0.073**	0.036	0.127***	0.048*	0.102**
	(0.031)	(0.038)	(0.036)	(0.027)	(0.047)
Control variables†	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	3087	953	477	2648	614
Adjusted R-squared	0.059	0.098	0.150	0.069	0.119
First stage:					
MIC2025	7.574***	9.284***	6.536***	8.193***	7.255***
	(0.384)	(0.406)	(0.561)	(0.403)	(0.536)
F-statistics	389.25	524.01	135.84	413.25	183.28

This table presents the identification check in Section 4.2. Column (1) uses the full sample. Columns (2) and (3) limit the sample to the counties located in red and blue states, respectively. Red and blue states were designated based on previous presidential election results (see Section 3.1 for details). Columns (4) and (5) limit the sample to the counties having incumbents all from one single party. Counties split across congressional districts are kept, and all their incumbents are considered (see Section 3.1 for details). † Control variables are the same as in Table 2. Robust errors are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.010.

with China in the same fashion and reach similar time trends, as displayed in the two right-side panels of Figure 4. The lack of time trend around the year 2015 indicates that the US neither imported more nor exported less MIC2025-related products when the Chinese government released MIC2025.

The above examination of aggregated trade statistics might not be sensitive enough to detect county-product level trends. We next specify the following regression to examine US imports and

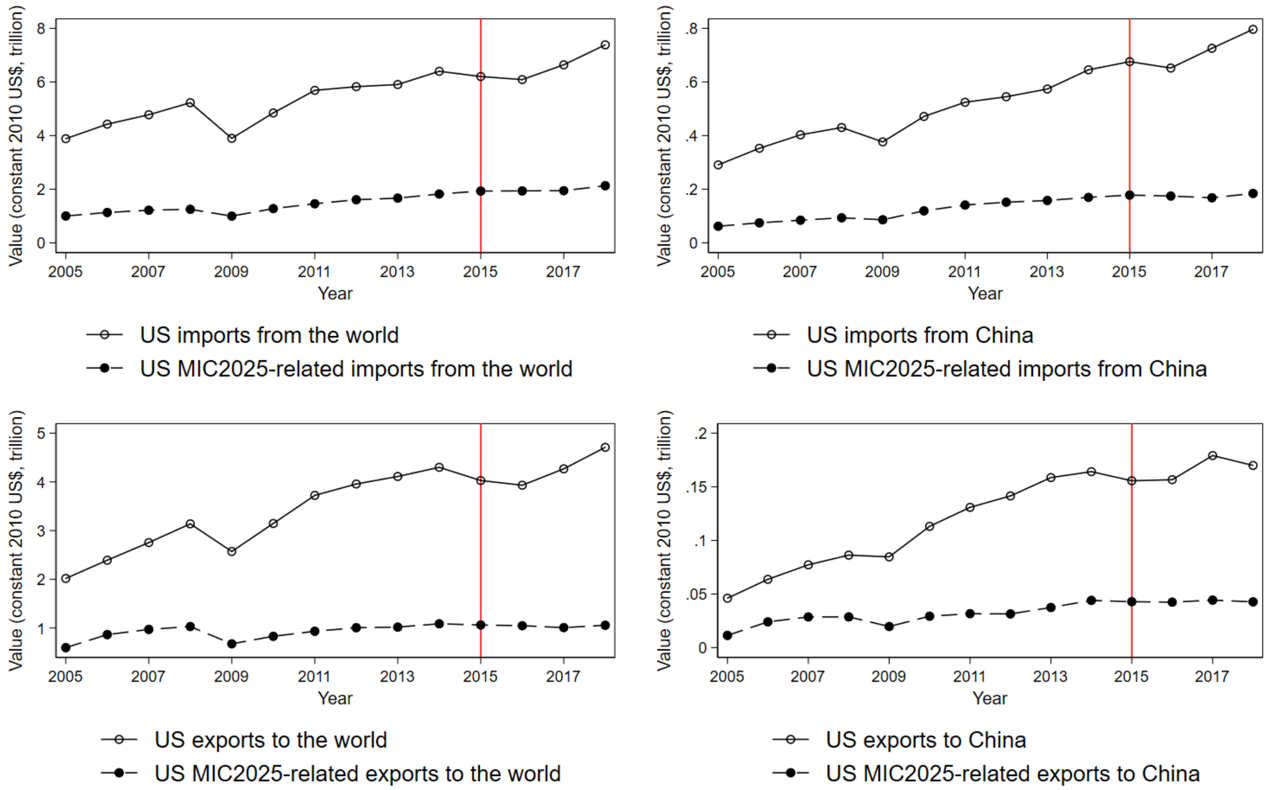

Figure 4: US Imports and Exports of MIC2025-related Products

This figure is part of the identification check in Section 4.3. The trends in the US imports and US exports of products related to China's MIC2025 are plotted across years. 2015 (marked) is the year when MIC2025 was released by the Chinese government.

exports of MIC2025-related products:

$$\ln T_{pt} = \mu + \omega MIC2025_p \times \mathbb{I}(t \geq 2015) + \lambda_{p4} + \lambda_t + \epsilon_{pt}. \tag{9}$$

where T_{pt} is either US exports or US imports of product p in year t. The indicator variable $\mathbb{I}(t \geq 2015)$ captures the presence of MIC2025 in China, and our parameter of interest is ω. Each observation is associated with a six-digit product p in year t, while $MIC2025_p$ remains to be at the four-digit product level as before. A constant term μ, a four-digit product fixed effect λ_{p4}, and a year fixed effect λ_t are included in the regression. The results are reported in Table 10, for the US trade with the rest of the world (columns (1)-(2)) and the US trade with China (columns (3)-(4)).[20] Again, we do not find evidence of an association between the MIC2025 product list and US trade performance.

[20]The difference in sample size between columns (1)-(2) and columns (3)-(4) is small, because most of the product varieties in US foreign trade relate to China. This reflects the intensive outsourcing activities mentioned earlier.

Table 10: Competing Explanation III (US Exports and Imports of MIC2025-related Products)

	(1)	(2)	(3)	(4)
	From/to the world		From/to China	
Dep. variable	ln(Imports)	ln(Exports)	ln(Imports)	ln(Exports)
MIC2025 × After-2015 dummy	0.309	-0.241	0.012	-0.005
	(0.188)	(0.270)	(0.024)	(0.033)
Observations	16,751	16,751	17,137	17,137
Adjusted R-squared	0.873	0.750	0.941	0.895
4-digit HS product FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

This table presents the identification check in Section 4.3. Each observation corresponds to one product-year duplet. The data cover the years 2005 to 2018. 2015 is the year when the Chinese government launched MIC2025. Robust errors are double-clustered at the two-digit product code level and the year level. None of the coefficients in the table are statistically significant at the 10 percent or lower levels.

Notice that we are not arguing that the Chinese government randomly chose industries to be included in its MIC2025. The Chinese government is known to have chosen industries with technological potentials for its MIC2025. These Chinese industries could become competitors of their US peers in the future, and the Trump administration applied additional tariffs on them. The potentials of these Chinese industries do not undermine the validity of MIC2025 as our instrument so long as they had not already harmed American voters by the time of the midterm elections. The US trade statistics in Figure 4 and Table 10 do not support such materialized harms by the time of the midterm elections.

4.4 Pre-trends in American Politics

Counties heavily exposed to Trump's China tariffs might be on different political trajectories from other counties. Our previous results rest primarily on cross-county variations and thus may not detect differential preexisting trends across counties. To address this concern, we apply our regression specification (3) to the previous political cycle 2014-2016. 2014 and 2016 were both election years for the house, and 2016 was also the year when Donald Trump was elected president. In this pre-trend check, we replace the dependent variable $R_{c,2018} - R_{c,2016}$ in regression specification (3) with $R_{c,2016} - R_{c,2014}$, and keep the rest of the regression specification the same as before.[21]

[21] The sample size decreases by two observations because the 2014 house election results for Pasco, Florida and Delta, Texas are missing in the Dave Leip Atlas database.

Table 11: Competing Explanation IV (Checks on Pre-trends in American Politics)

	(1)	(2)	(3)
Dep. variable:	Difference in the Republican vote share (2016 minus 2014)		
Sample:	All	Red	Blue
Panel A: OLS Results			
Trump tariff exposure	-0.006	-0.002	-0.007
	(0.005)	(0.002)	(0.012)
Control variables†	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Observations	3085	952	477
Adjusted R-squared	0.213	0.318	0.265
Panel B: 2SLS Results			
Second stage:			
Trump tariff exposure	-0.007	-0.002	-0.011
	(0.006)	(0.003)	(0.015)
Control variables†	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Observations	3085	952	477
Adjusted R-squared	0.094	0.176	0.201
First stage:			
MIC2025	54.979***	98.810***	44.221***
	(7.726)	(8.193)	(2.418)
F-statistics	50.64	145.46	334.42

This table presents the identification check in Section 4.4. Column (1) uses the full sample. Its sample size 3,085 is smaller than the sample size 3,083 in previous tables, because the 2014 house election statistics for Pasco, Florida and Delta, Texas are missing in the Dave Leip Atlas database. Columns (2) and (3) limit the sample to the counties located in red and blue states, respectively. Red and blue states were designate based on previous presidential election results (see Section 3.1 for details). † Control variables are the same as in Table 2. Robust errors are clustered at the state level. *** p<0.010.

Notice that there is now a time-period mismatch between the left-hand side of the regression (2014 to 2016) and the right-hand side of the regression (2016 to 2018). This mismatch is purposefully designed to detect pre-trends. Suppose that there existed pro-Republican momenta in certain counties before Trump was elected president, and that Trump, after being elected and inaugurated, tailored a China-tariff schedule to reward those counties. Then, the reversed causality would be captured by this "mismatch regression." The results are reported in Table 11.[22] The pre-

[22]Unlike the previous tables, Table 11 does not have columns related to Republican and Democratic incumbents. This is because the incumbents in the year 2018 (elected in the year 2016) were not incumbents in the year 2016 (elected in

viously significant effects of Trump's China tariffs on the Republican voting shares all disappear. This finding confirms that pre-trends, if existing, cannot explain our main findings.

5 Counterfactual Analysis

The Republican Party lost its house majority in the 2018 midterm elections. Heading into the midterm, Republicans controlled the house with a 235-193 majority, and there were seven vacant seats in the house prior to the elections. All 435 house seats were up for election, corresponding to 435 congressional districts in the country. Ultimately, Republicans filled 200 of them, while Democrats filled 235, equating to a net loss for Republicans of 35 seats. As shown in Section 3, the China tariffs helped the Republicans at the midterm. We now quantitatively assess how many of the seats won by Republicans would have been lost without Trump's China tariffs. In other words, the Republicans would have performed worse without the tariffs and we below estimate how worse the counterfactual outcome would have been.

Notationally, the Republican candidate of congressional district d won the election if she received a larger share of the district's votes, namely if

$$Repub\_Share_d \equiv \frac{Repub\_Votes_d}{Total\_Votes_d} > Dem\_Share_d \equiv \frac{Dem\_Votes_d}{Total\_Votes_d}. \tag{10}$$

Likewise, she lost the election if the inequality reverses. Next we use the 2SLS estimate $\hat{\alpha}_1^{2SLS}$ to construct a counterfactual share of the Republican candidate in county c:

$$\widetilde{R}_{c,2018} = R_{c,2018} - \hat{\alpha}_1^{2SLS} \times TrumpTariffExpo_c. \tag{11}$$

The above formulation of $\widetilde{R}_{c,2018}$ follows from regression specification (3). We then follow equation (10) to construct the district's counterfactual Republican vote share:

$$\widetilde{Repub\_Share}_d \equiv \frac{\sum_{c\in d} \widetilde{R}_{c,2018} \times Total\_Votes_c}{Total\_Votes_d}. \tag{12}$$

The $\{c \in d\}$ in equation (12) denotes all counties associated with congressional district d. We define a county as associated with a congressional district as long as part of the county is located in the congressional district. The counterfactual election outcome in a congressional district stems from the application of inequality (10) to all associated counties in the congressional district, rather than to counties encompassed by the congressional district. This is because the key parameters used in equation (11) come from the 2SLS regressions run at the county level (recall Table 5).[23] Al-

the year 2014).

[23] As noted earlier, the tariff exposure cannot be disaggregated to a sub-county level because the County Business Patterns (CBP) database does not provide employment data at sub-county levels.

though associated counties might be double-counted across congressional districts, the potential inaccuracy applies to both sides of inequality (10) and therefore counteract each other to mitigate potential double-counting.

As counterparts of shares (11) and (12), we have counterfactual Democratic candidate vote shares at the county level

$$\widetilde{D}_{c,2018} = D_{c,2018} + \hat{\alpha}_1^{2SLS} \times TrumpTariffExpo_c, \tag{13}$$

and at the district level

$$\widetilde{Dem\_Share}_d \equiv \frac{\sum_{c \in d} \widetilde{D}_{c,2018} \times Total\_Votes_c}{Total\_Votes_d}. \tag{14}$$

The $D_{c,2018}$ in equation (13) is the share of votes received by Democratic house candidates in county c.[24] We use the relative sizes of $\widetilde{Repub\_Share}_d$ and $\widetilde{Dem\_Share}_d$ to decide which party's candidate would have won without Trump's China tariffs; that is, the party with a greater district-level counterfactual share would have won congressional district d without Trump's China tariffs.

Since Trump's China tariffs favored the Republican candidates, the counterfactual analysis is relevant only to the congressional districts where Republican candidates won. In particular, the congressional districts where Republicans might have lost are the places where Trump's China tariffs made a difference. We located the districts where Republicans narrowly won listed by the analysis team of *The New York Times*, whose original data sources include the Cook Political Report and the Associated Press. Details of these districts are provided in Appendix A.1. For these districts, we conduct the counterfactual analysis outlined above.

For robustness, we use three versions of $\hat{\alpha}_1^{2SLS}$ in the construction of county-level counterfactual vote shares (11) and (13), including $\hat{\alpha}_1^{2SLS}$ itself (0.010, as in column (1) of Panel A, Table 5) and $\hat{\alpha}_1^{2SLS}$ plus and minus one standard error (0.005). The plus (respectively, minus) one standard error magnitude tends to overstate (respectively, understate) the positive impact of the China tariffs on the Republican winnings, but they join $\hat{\alpha}_1^{2SLS}$ to enable us to assess a robust range of the effect. The results from our counterfactual analysis are reported in Panel A of Table 12. Out of the 27 districts, two to four (Georgia District 7, New York District 27, California District 50, and Texas District 23) would have been lost without Trump's China tariffs. We also look into the congressional districts flipped by Republicans (i.e., districts that switched from Democratic to Republican, according to the same data source as above). The results are reported in Panel B of Table 12. Out of the nine districts, one to two (North Carolina District 9 and Pennsylvania District 1) would not have flipped.[25]

[24] $D_{c,2018}$ is not necessarily equal to $1 - R_{c,2018}$ because of the presence of other political parties in county c or its congressional district d.

[25] The outcome of the North Carolina District 9 election was undecided until September 2019.

Table 12: Counterfactual Analysis

Panel A: Congressional Districts Narrowly Won by Republicans

	Panel A1			Panel A2			Panel A3		
Dist.	Rep share w/o China tariffs	Dem share w/o China tariffs	Counterfactual outcome	Rep share w/o China tariffs	Dem share w/o China tariffs	Counterfactual outcome	Rep share w/o China tariffs	Dem share w/o China tariffs	Counterfactual outcome
Alaska	0.531	0.465	Win	0.531	0.465	Win	0.531	0.465	Win
Calif. 50	0.506	0.494	Win	0.494	0.506	Lose	0.482	0.518	Lose
Fla. 6	0.562	0.438	Win	0.561	0.439	Win	0.560	0.440	Win
Fla. 16	0.544	0.456	Win	0.543	0.457	Win	0.542	0.458	Win
Fla. 18	0.542	0.458	Win	0.542	0.458	Win	0.541	0.459	Win
Fla. 25	0.602	0.398	Win	0.600	0.400	Win	0.598	0.402	Win
Ga. 7	0.498	0.502	Lose	0.496	0.504	Lose	0.494	0.506	Lose
Ill. 12	0.515	0.455	Win	0.514	0.456	Win	0.513	0.456	Win
Ill. 13	0.503	0.497	Win	0.503	0.497	Win	0.502	0.498	Win
Iowa 4	0.503	0.470	Win	0.502	0.471	Win	0.502	0.471	Win
Mich. 6	0.502	0.458	Win	0.501	0.459	Win	0.500	0.459	Win
Minn. 8	0.507	0.452	Win	0.506	0.453	Win	0.505	0.454	Win
Mo. 2	0.508	0.476	Win	0.505	0.479	Win	0.501	0.483	Win
Mont.	0.509	0.463	Win	0.508	0.463	Win	0.508	0.463	Win
Neb. 2	0.508	0.492	Win	0.506	0.494	Win	0.504	0.496	Win
N.Y. 24	0.524	0.474	Win	0.523	0.476	Win	0.522	0.477	Win
N.Y. 27	0.488	0.491	Lose	0.485	0.494	Lose	0.481	0.497	Lose
N.C. 2	0.512	0.459	Win	0.510	0.461	Win	0.509	0.462	Win
Ohio 1	0.509	0.473	Win	0.505	0.477	Win	0.501	0.481	Win
Pa. 16	0.514	0.475	Win	0.511	0.477	Win	0.509	0.480	Win
Tex. 22	0.506	0.472	Win	0.499	0.479	Win	0.492	0.487	Win
Tex. 23	0.489	0.489	Win	0.487	0.492	Lose	0.485	0.494	Lose
Va. 5	0.531	0.467	Win	0.531	0.467	Win	0.530	0.468	Win
Wash. 3	0.525	0.475	Win	0.523	0.477	Win	0.521	0.479	Win
Wash. 5	0.546	0.454	Win	0.545	0.455	Win	0.544	0.456	Win
W.Va. 3	0.563	0.437	Win	0.563	0.437	Win	0.563	0.437	Win
Wis. 1	0.542	0.426	Win	0.539	0.429	Win	0.535	0.433	Win

This table presents the counterfactual analysis in Section 5. Panel A1 uses the original coefficient minus one standard error (0.005); Panel A2 uses the original coefficient (0.010); Panel A3 uses the original coefficient plus one standard error (0.015). Coefficient and standard error are from column (1) in Panel A of Table 5.

Table 12: Counterfactual Analysis, Continued

Panel B: Congressional Districts Flipped by Republicans									
	Panel B1			Panel B2			Panel B3		
Dist.	Rep share w/o China tariffs	Dem share w/o China tariffs	Counter. outcome	Rep share w/o China tariffs	Dem share w/o China tariffs	Counter. outcome	Rep share w/o China tariffs	Dem share w/o China tariffs	Counter. outcome
Fla.15	0.528	0.472	Win	0.525	0.474	Win	0.523	0.477	Win
Kan.2	0.476	0.468	Win	0.476	0.469	Win	0.475	0.469	Win
Ky.6	0.509	0.479	Win	0.508	0.480	Win	0.507	0.480	Win
Minn.1	0.501	0.497	Win	0.500	0.498	Win	0.500	0.498	Win
N.C.9	0.490	0.492	Lose	0.487	0.495	Lose	0.484	0.497	Lose
N.C.13	0.512	0.458	Win	0.509	0.462	Win	0.506	0.465	Win
Ohio 12	0.512	0.474	Win	0.510	0.476	Win	0.509	0.478	Win
Pa.1	0.508	0.492	Win	0.504	0.496	Win	0.499	0.501	Lose
Pa.10	0.512	0.488	Win	0.510	0.490	Win	0.508	0.492	Win

This table presents the counterfactual analysis in Section 5. Panel B1 uses the original coefficient minus one standard error (0.005); Panel B2 uses the original coefficient (0.010); Panel B3 uses the original coefficient plus one standard error (0.015). Coefficient and standard error are from column (1) in Panel A of Table 5.

6 Concluding Remarks

The Republican Party lost its majority in the US House of Representatives in its 2018 midterm elections. The China tariffs launched by the Republican president earlier that year did not cause defeat for Republicans but to the contrary, mitigated Republican losses. We find that counties that were exposed more to Trump's China tariffs, with all else held equal, gave stronger support to the Republican house candidates in their districts. In other words, the Republican party would have lost more seats without Trump's China tariffs. As economists, who practice a science of *ceteris paribus*, we have the tools to identify political gains for the Republicans from Trump's China tariffs. These gains have been mentioned by some political commentators (e.g., Mayeda (2018) and Rappeport (2020)), but we qualitatively confirm them, quantitatively estimate them, and conduct counterfactual predictions on the election outcome for the Republicans if there were no China tariffs.

We undertook this study because estimating the effect of the tariffs on the Republican midterm is an interesting economic question. The fact that a specific trade policy influences nationwide political elections offers strong evidence of the redistributive effects of international trade. These redistributive effects were established in theory a century ago but have been believed to be benign in practice since then. Our findings resonate with the recent economic studies on the "China Syndrome." As noted in the introduction, the topic of China started being part of US campaign narratives in the early 1980s, which was far earlier than the onset of the China Syndrome. Insidious onset is perhaps an unrecognized symptom of the syndrome. The reason for the delayed awareness of the syndrome in both academic and policy arenas is an avenue for future research.

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"Trump, China, and the Republicans"
Appendices

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A.1 Details of data

Trump's China tariffs. The product lists and tariff rates were published at the Federal Register (www.federalregister.gov) as noted in Section 2.1 of the main text. They can also be downloaded from the website of the US Trade Representative (USTR). See https://ustr.gov/issue-areas/enforcement/section-301-investigations/section-301-china/300-billion-trade-action. On July 6, 2018, Tranche 1 took effect. On August 23, 2018, Tranche 2 took effect, with five product codes (eight-digit HS codes) exempted. The five product codes belong to alginic acid, splitting machines, containers, floating docks, and microtomes. On September 24, 2018, Tranche 3 took effect, with 297 product codes partially or fully exempted. The 297 products include some consumer electronics products (such as smart watches and bluetooth devices), some chemical inputs for manufactured goods, textiles and agriculture, some health and safety products (such as bicycle helmets), and some child safety furniture (such as car seats and playpens). On the same date, the Trump administration decided to raise the additional tariffs listed in Tranche 3 from 10 percent to 25 percent, effective January 1, 2019. The actual effective date was later postponed twice, in December 2018 and February 2019. They finally became effective on May 10, 2019. The effective tariffs used in our robustness checks refer to those that had been effective by the time of the midterm elections (November 6, 2018), namely the 10 percent additional tariffs, effective since September 24, 2018.

House election results. The house election results were purchased from *Dave Leip Atlas* (www.uselectionatlas.org), a company that collects data on US public office elections from public sources and compiles them into commercial databases. The election results in Alaska were reported by district rather than by county. We converted the results from Alaska to the county level through the correspondence table provided by the US Census Bureau. See www2.census.gov/geo/relfiles/cdsld14/02/co_ll_02.txt.

County Business Patterns (CBP). The data on manufacturing employment across counties in 2016 were downloaded from the County Business Patterns (CBP) database maintained by the US Census Bureau. See www.census.gov/programs-surveys/cbp/data/datasets.html.

American Community Survey (ACS). The data were downloaded at factfinder.census.gov/faces/nav/jsf/pages/searchresults.xhtml?refresh=t. We merged the 2013-2017 five-year estimates with the 2018 house election results, and merged the 2011-2015 five-year estimates with the 2016 election results.

Association of Religion Data Archives (ARDA). The ARDA data were downloaded at www.thearda.com/Archive/ChCounty.asp. Specifically, we use the Longitudinal Religious Congregations and Membership File 1980-2010.

Congressional districts narrowly won and flipped by Republicans. The lists of the districts can be found in the website of *The New York Times*: www.nytimes.com/interactive/2018/11/06/us/elections/results-house-elections.html. The original data sources include the Cook Political Report and the Associated Press. The first list is labeled as districts where "Republicans expected to win narrowly." Districts NY-11 and SC-1 in the list were lost by Republicans and thus dropped from our counterfactual analysis. The second list is labeled as "Tossup seats." We extracted the tossup cases in which Democrats lost to Republicans.

H-1B visa data. The H-1B visa approvals data can be found in the website of the US Citizenship and Immigration Services (USCIS). We downloaded the total approvals for the years 2017 and 2018 from the H-1B Employer Data Hub: https://www.uscis.gov/tools/reports-and-studies/h-1b-employer-data-hub.

PWBM. The Penn Wharton Budget Model's (PWBM) estimates come from Table 2 in the report *The Tax Cuts and Jobs Act, as Reported by Conference Committee (12/15/17): Tax Effects by Industry.* The estimates are provided by two-digit (NAICS) sector. The report is publicly available at https://budgetmodel.wharton.upenn.edu/issues/2017/12/15/effective-tax-rates-by-industry.

China's retaliatory tariffs. The product lists and tariff rates can be downloaded from the website of the Ministry of Finance (MOF) of China. The Department of Tariffs at the MOF regularly publish *Announcements of the Customs Tariff Commission of the State Council* (http://gss.mof.gov.cn). The Announcements #2018-5, #2018-6, and #2018-7 are related to the retaliatory tariffs and thus are used as our data sources.

A.2 Results from single party incumbent counties

As noted in Sections 3.1 and 3.2, we experiment with decreasing the sample by excluding counties with incumbent representatives from different parties. This decreased sample solution is an alternative to the expanded solution adopted in columns (4)-(5) of Table 2 and Table 5. Consider a county that has more than one congressional district. If the incumbents in all these districts are from the same party, the county remains in the sample. Otherwise, the county is excluded from the sample. Counties that have only one congressional district are kept in the sample because they do not have multiple incumbents and thus have no incumbents from different parties.

The results from the sample described above are reported in Table A2. Columns (1) and (2) in the table follow the specifications in columns (4) and (5) of Table 2, while columns (3) and (4) in the table follow the specifications in columns (4) and (5) of Table 5. The results are highly consistent with those presented in Tables 2 and 5. That is, a larger exposure to Trump's China tariffs raises the support for local Republican candidates in counties with Democratic incumbents but not in counties with Republican incumbents.

A.3 Details of the Made in China 2025 Initiative

The Made-in-China 2025 Initiative (hereafter, MIC2025) was released by the State Council of China on May 19, 2020. The full text of the MIC2025 document is publicly available on the Chinese Central Government's website: http://www.gov.cn/zhengce/content/2015-05/19/content_9784.htm. The initiative aims to transform China into a global manufacturing leader in the production of high-technology products. It encourages the use of private and state funds to conduct research and development (R&D) and purchase global firms. It explicitly identifies ten focal industries with strategic value. We manually matched these ten industries to 109 four-digit HS codes through the similarities between the industry descriptions in the MIC2025 document and the product descriptions of the four-digit HS codes (publicly available on the UN Statistics Division's website, see https://unstats.un.org/unsd/tradekb/Knowledgebase/14).

Our method of manually matching the MIC2025 industries with HS codes is based on three types of matches. First, we identify matches based on direct text relevance. For example, the MIC2025 document lists "advanced rail equipment" as one focal industry, and HS code 8601 is for "rail locomotives; powered from an external source of electricity or by electric accumulators." Therefore, HS code 8601 is labeled as a MIC2025 product. The second type of match is based on text inference involving the MIC2025 descriptions. The MIC2025 document lists examples of products or technologies for each focal industry. For instance, the MIC2025 lists "new materials" as a focal industry and uses "inorganic nonmetallic materials" as an example product. Correspondingly, we count HS code 3801 ("artificial graphite; colloidal or semi-colloidal graphite; preparations based on graphite or other carbon in the form of pastes, blocks, plates or other semi-manufactures") as a MIC2025 product because graphene, as a new material, belongs to HS code 3801 (it has a unique six-digit HS code 380190). The third type of match is based on text inference of the HS descriptions. For instance, "casein, caseinates, and other casein derivatives; casein glues" (HS code 3501) is an intermediate input of pharmaceutical products. We therefore associate it with the biomedicine industry in the MIC2025 document. The MIC2025 document also mentions military products but does not categorize them into a separate focal industry, and we therefore categorize them into an "other" industry.

Details on the method of manually matching the ten MIC2025 focal industries with the four-digit HS codes are provided below.

Industry 1. Next-generation information technology (4 codes): 8517, 8526, 8529, 9803.

Industry 2. High-end numerical control machinery and robotics (6 codes): 8428, 8471, 8474, 8477, 8509, 9032.

Industry 3. Aerospace and aviation equipment (3 codes): 8802, 8803, 8805.

Industry 4. Maritime engineering equipment and high-tech maritime vessel manufacturing (12 codes): 8406, 8407, 8408, 8409, 8410, 8411, 8412, 8482, 8483, 8901, 8903, 8905.

Industry 5. Advanced rail equipment (10 codes): 7302, 8601, 8602, 8603, 8604, 8605, 8606, 8607, 8608, 8701.

Industry 6. Energy-saving and new energy vehicles (1 code): 8703.

Industry 7. Electrical equipment (27 codes): 8454, 8456, 8458, 8459, 8461, 8462, 8463, 8468, 8479, 8480, 8486, 8501, 8502, 8503, 8504, 8511, 8515, 8516, 8535, 8536, 8537, 8538, 8542, 8543, 8546, 8547, 9028 .

Industry 8. New materials (30 codes): 2804, 2805, 2810, 2811, 2812, 2813, 2846, 2848, 2849, 2850, 2919, 2920, 3506, 3801, 3810, 3816, 3826, 4002, 6815, 6914, 7006, 7019, 7202, 7505, 8105, 8113, 8401, 8544, 8545, 9001.

Industry 9. Biomedicine and high-performance medical devices (8 codes): 2207, 3004, 3501, 3502, 3907, 9018, 9021, 9022.

Industry 10. Agricultural machinery and equipment (1 code): 8433.

Other. (7 codes) 8710, 9301, 9302, 9303, 9304, 9305, 9306.

A.4 Derivation of equation (7)

For convenience, define $\Delta R_c \equiv R_{c,2018} - R_{c,2016}$. Suppose the direct and indirect effects of Δt_p^{Trump} on ΔR_c are π_{direct} and $\pi_{indirect}$, respectively. That is,

$$\pi_{direct} \equiv \frac{\partial \Delta R_c}{\partial \Delta t_p^{Trump}}, \tag{A.1}$$

and

$$\pi_{indirect} \equiv \sum_{p' \in c} \underbrace{\frac{\partial \Delta R_c}{\partial \Delta t_{p'}^{China}}}_{\substack{\text{political feedback} \\ \text{to China's retaliation}}} \underbrace{\left(\sum_{p \in US} \frac{\partial \Delta t_{p'}^{China}}{\partial \Delta t_p^{Trump}} \right)}_{\substack{\text{China's retaliation} \\ \text{function}}} \tag{A.2}$$

Then, with all else held equal, a differential in ΔR_c can be written as

$$d\Delta R_c = \sum_{p \in c} \frac{L_{c,j(p)}}{L_{j(p)}} \pi_{direct} d\Delta t_p^{Trump} + \sum_{p \in c} \frac{L_{c,j(p)}}{L_{j(p)}} \pi_{indirect} d\Delta t_p^{Trump}. \tag{A.3}$$

Equation (1) implies

$$dTrumpTariffExpo_c = \sum_{p \in c} \frac{L_{c,j(p)}}{L_{j(p)}} d\Delta t_p^{Trump}. \tag{A.4}$$

So, equation (A.3) can be rewritten as

$$\frac{\partial \Delta R_c}{\partial TrumpTariffExpo_c} = \pi_{direct} + \pi_{indirect}. \tag{A.5}$$

Equation (A.5), with equation (A.2) inserted, gives equation (7) .

A.5 Additional tables and figures

Table A1 is discussed in Section 2.1 of the main text. Table A2 is discussed in Appendix A.2. Tables A3 and A4 are discussed in Section 4.1 of the main text.

Table A1: Skewness in the Aggregation of Product Codes

Number of eight-digit product codes listed under six-digital product codes	Cases	Percent (%)	Cum. (%)
1	2472	64.41	64.41
2	686	17.87	82.28
3	259	6.75	89.03
4	156	4.06	93.10
5	88	2.29	95.39
6	62	1.62	97.00
7	33	0.86	97.86
8	32	0.83	98.70
9	16	0.42	99.11
10	5	0.13	99.24
11	11	0.29	99.53
12	5	0.13	99.66
13	3	0.08	99.74
14	2	0.05	99.79
15	3	0.08	99.87
16	2	0.05	99.92
19	1	0.03	99.95
20	1	0.03	99.97
31	1	0.03	100
Total	3838		

Table A2: Results from the Decreased Sample

Estimation method	(1) Republican incumbent	(2) Democratic incumbent	(3) Republican incumbent	(4) Democratic incumbent
Dep. variable is differenced republican vote share				
Trump tariff exposure	-0.003	0.065**	-0.021	0.082**
	(0.010)	(0.031)	(0.029)	(0.034)
Estimation method	OLS	OLS	2SLS	2SLS
Control variables†	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	2472	438	2472	438
Adjusted R-squared	0.207	0.403	0.051	0.152
			First stage	
MIC2025			32.469***	27.316***
			(4.937)	(2.285)

This table is part of Appendix A.2. It is related to columns (4) to (5) in both Table 2 (OLS) and Table 5 (2SLS). Unlike in those four columns, counties split across congressional districts are excluded here. † Control variables are the same as in Table 2. Robust errors are clustered at the state level. ** p<0.05, *** p<0.01.

Table A3: Competing Explanation IA — A Further Check
H-1B Policy Change (IV reconstructed by group at the same time)

	(1)	(2)	(3)	(4)	(5)
Dep. variable:	Difference in the Republican vote share (2018 minus 2016)				
Sample:	All	Red	Blue	Republican incumbent	Democratic incumbent
OLS Results — H-1B high group					
Trump tariff exposure	0.014**	0.009	0.022***	0.010*	0.018*
	(0.007)	(0.005)	(0.005)	(0.006)	(0.009)
Observations	3087	953	477	2648	614
Adjusted R-squared	0.175	0.128	0.338	0.180	0.255
OLS Results — H-1B low group					
Trump tariff exposure	0.015	0.009*	0.023	0.009	0.019
	(0.011)	(0.005)	(0.016)	(0.009)	(0.013)
Observations	3087	953	477	2648	614
Adjusted R-squared	0.172	0.128	0.326	0.178	0.249
2SLS Results — H-1B high group					
Second stage:					
Trump tariff exposure	0.015**	0.004	0.026***	0.011*	0.022**
	(0.007)	(0.008)	(0.007)	(0.006)	(0.010)
Observations	3087	953	477	2648	614
Adjusted R-squared	0.057	0.097	0.188	0.066	0.119
First stage:					
MIC2025	39.428***	69.666***	33.657***	43.782***	37.982***
	(3.496)	(8.591)	(1.490)	(3.768)	(4.027)
2SLS Results — H-1B low group					
Second stage:					
Trump tariff exposure	0.014*	0.010*	0.036*	0.007	0.013
	(0.10)	(0.005)	(0.017)	(0.008)	(0.011)
Observations	3087	953	477	2648	614
Adjusted R-squared	0.053	0.099	0.171	0.063	0.112
First stage:					
MIC2025	132.732***	140.685***	109.311***	133.370***	131.317***
	(5.543)	(1.632)	(10.310)	(6.258)	(5.540)

This table presents a further identification check mentioned at the end of Section 4.1. Here, not only the tariff exposure but also the instrument is constructed by (high/low) group. Column (1) uses the full sample. Columns (2) and (3) limit the sample to the counties located in red and blue states, respectively. Red and blue states were designated based on previous presidential election results (see Section 3.1 for details). Columns (4) and (5) limit the sample to the counties having incumbents all from one single party. Counties split across congressional districts are kept, and all their incumbents are considered (see Section 3.1 for details). Control variables (the same as in Table 2) and state fixed effects are included. Robust errors are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.010.

Table A4: Competing Explanation IB — A Further Check
Corproate Tax Savings (IV reconstructed by group at the same time)

	(1)	(2)	(3)	(4)	(5)
Dep. variable:	Difference in the Republican vote share (2018 minus 2016)				
Sample:	All	Red	Blue	Republican incumbent	Democratic incumbent
OLS Results — Tax saving high group					
Trump tariff exposure	0.012	0.007*	0.028***	0.008	0.014
	(0.009)	(0.003)	(0.009)	(0.007)	(0.010)
Observations	3087	953	477	2648	614
Adjusted R-squared	0.173	0.129	0.333	0.178	0.249
OLS Results — Tax saving low group					
Trump tariff exposure	0.017**	0.013	0.024***	0.013*	0.024**
	(0.007)	(0.010)	(0.005)	(0.007)	(0.011)
Observations	3087	953	477	2648	614
Adjusted R-squared	0.174	0.127	0.334	0.180	0.256
2SLS Results — Tax saving high group					
<u>*Second stage:*</u>					
Trump tariff exposure	0.026**	0.007	0.041***	0.021**	0.029*
	(0.011)	(0.004)	(0.012)	(0.010)	(0.017)
Observations	3087	953	477	2648	614
Adjusted R-squared	0.047	0.100	0.179	0.055	0.102
<u>*First stage:*</u>					
MIC2025	71.410***	187.047***	57.534***	80.547***	73.092***
	(13.217)	(15.318)	(1.857)	(16.080)	(16.591)
2SLS Results — Tax saving low group					
<u>*Second stage:*</u>					
Trump tariff exposure	0.016*	0.008	0.031***	0.008	0.025**
	(0.008)	(0.012)	(0.008)	(0.007)	(0.012)
Observations	3087	953	477	2648	614
Adjusted R-squared	0.056	0.098	0.182	0.065	0.121
<u>*First stage:*</u>					
MIC2025	41.380***	45.445***	36.756***	43.785***	39.854***
	(1.262)	(3.697)	(2.114)	(0.960)	(2.627)

This table presents a further identification check mentioned at the end of Section 4.1. Here, not only the tariff exposure but also the instrument is constructed by (high/low) group. Column (1) uses the full sample. Columns (2) and (3) limit the sample to the counties located in red and blue states, respectively. Red and blue states were designated based on previous presidential election results (see Section 3.1 for details). Columns (4) and (5) limit the sample to the counties having incumbents all from one single party. Counties split across congressional districts are kept, and all their incumbents are considered (see Section 3.1 for details). Control variables (the same as in Table 2) and state fixed effects are included. Robust errors are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.010.