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. Donald Trump, the 45th US president, held 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. 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 occur halfway through a president's four-year term, was the first political appraisal by American voters of the Republican party's turnabout on trade policies.

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

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support in 2018 than in 2016 in counties with greater exposure to Trump's China tariffs. Then we endeavor to identify the underlying causality. Trump's China tariffs specifically targeted China's Made-in-China 2025 Initiative (hereafter, MIC2025). The MIC2025, released by the Chinese State Council in 2015 as a guide for domestic investments, emphasized industrially significant technologies in various sectors. This initiative served as a critical motivation for Trump's China tariffs, as made clear by the Trump administration when it announced the tariffs. As a proposal not yet developed into concrete 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 greater exposure to Trump's China tariffs raises local support for Republican house candidates. The impact of Trump's China tariffs on Republican house candidates is 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 areas where voters had previously leaned towards Democratic politicians.

We also conduct a counterfactual analysis by subtracting the estimated political gains for Republican house candidates from the votes they received to examine how the midterm election outcomes would have changed without Trump's China tariffs. 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 five congressional districts that they narrowly won and one congressional district that they flipped from Democratic to Republican control at the midterm.

International trade, although beneficial to each participating nation as a whole, does not necessarily benefit every citizen in the participating nations. Most trade policies are contentious, since they create winners and losers. Gains and losses from international trade have been extensively documented as an important factor on policy making (Blonigen and Figlio, 1998; Baldwin and Magee, 2000; Conconi, Facchini, and Zanardi, 2012, 2014) as well as on political elections (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 interest in an international political setting. In a trade war, not only do nations act strategically to attack one another, but so too do interest groups within each nation 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 Republicansponsored 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 other strategic moves of the country, with retaliations by trade partners expected and taken into account by the country. These actions are all endogenous for governments involved in a trade war. Researchers have come up with various approaches to addressing such endogeneity. Among the few existing empirical studies on the midterm elections of 2018, Fetzer and Schwarz (2021) and Chyzh and Urbatsch (2020) chose to examine how retaliation 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 reforms 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 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 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 thus 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 express their views 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 long before 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 as to whether a high-pitched voice followed by a low-pitched inaction on China issues was a strategy used by American politicians to maximize their total gains, including but not limited to winning elections. 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 otherwise 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, caused by 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 OLS and 2SLS results. In Section 4, we present a wide range of additional identification and robustness checks. In Section 5, we conduct a counterfactual study on the outcomes of the 2018 midterm house elections. In Section 6, we conclude.

2 Data

2.1 Trump's China Tariffs

Donald Trump, inaugurated as the 45th US president on 20 January 2017, instructed the United States Trade Representative (USTR) on 14 August 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 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 22 March 2018.[1] On the same date, Trump signed a presidential memorandum to announce that additional tariffs would be applied to Chinese products. On 3 April 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*

[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/issue-areas/enforcement/section-301-investigations/section-301-china/investigation. 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 media, since the US imports of these products from China in 2017 were worth 50 billion USD. On 18 June 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 10 July 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).

In the first document above, an additional tariff of 25 percent was applied to 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 to 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 were levied with the additional tariffs. There are 1,283 six-digit products that were imported by the US from China in 2017 but that 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 listed under each of them. Specifically, 2,472 of the six-digit product codes have only one corresponding eight-digit product code, 686 of them have two, 259 have three, and 421 have more than three corresponding codes. 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 her congressional district (hereafter, district). Districts are apportioned among states based on population. There are 435 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 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 single districts. We choose county-district as the unit of observation, which is a trade-off between two considerations. At one end, a county is the smallest possible unit of nationwide statistics in the US. Either aggregating county-level statistics to the district level, or disaggregating county-level statistics across districts, would necessitate making assumptions on the geographical distributions of voters within and across counties. Moreover, total votes received by each political party are administratively collected and recorded by counties (or originally collected by towns and then aggregated to counties, as practiced in some New England and Midwestern states). For these data reasons, the extant studies on the 2018 midterm house elections use county as the unit of observation (Blanchard et al., 2019; Chyzh and Urbatsch, 2020; Fetzer and Schwarz, 2021).[2] At the other end, we are aware that a district is the voting unit for house elections, including the 2018 midterm house elections. A county may correspond to multiple election outcomes if it contains more than one district for house elections. To strike a balance between these two considerations, we expand the sample to the county-district duplet level. Counties having multiple districts are treated as multiple observations, such that the election outcomes of a given multi-district county, either the same or different, are treated equally.

We would like to make three technical notes on the use of county-district duplet as our unit of observation. First, as mentioned earlier, 2,734 out of 3140 counties in our data have single districts, and therefore whether to use county or county-district duplet as the unit of observation makes a very limited difference. Second, we still call our sample county-level data, as each single-district county

[2]County is also chosen as the unit of observation in studies on other aspects of US politics and policies. 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), Blanchard et al. (2019), and Lake and Nie (2021).

constitutes a county observation and each multiple-district county constitutes multiple county observations. Third, as empirical experiments, we run our study with strictly county-level data (i.e., the district dimension is removed) and manually constructed district-level data (i.e., the county dimension is removed). The results are reported in Sections 4.4–4.5 as robustness checks.

The data on manufacturing employment across counties were downloaded from the County Business Patterns (CBP) database maintained by the US Census Bureau. The CBP data are published by the US Census Bureau at the county-industry level. The employment data we use are for the year 2010. 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 in our analysis. The county-level demographic statistics, along with population density and income inequality (Gini coefficient), were obtained from the American Community Survey (ACS) of the US Census Bureau. The religion-related data were obtained from the Association of Religion Data Archives (ARDA). In our regressions, we also control for exposure to China's industrial competition, obtained from the study by Autor et al. (2013). Detailed data sources are provided in Appendix A.1.

2.3 Exposure to Trump's China Tariffs

Our measure of county-level exposure to Trump's China tariffs is similar to the Bartik measure used in Autor et al. (2013) and Acemoglu et al. (2016), which has been widely used in the literature (e.g., Autor et al. (2020), Lu et al. (2018), and Pierce and Schott (2020)). We tailor their formula to our context, measuring county c's exposure to Trump's China tariffs with

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

where Δt_p^{Trump} is the additional tariff levied on product p. The rationale underlying this measure is as follows. Product p in county c receives tariff shock Δt_p^{Trump} if product p is made only in county c. Since product p may also be made in other counties, the shock is weighted by employment share $L_{c,p}/L_p$, namely the share of county c's employment related to product p in the national employment related to product p. For instance, if product p is made by two US counties, with a half related-employment share in each, then product p in county c receives half of the tariff shock Δt_p^{Trump}. Also, suppose that county c also produces product p'. Then the corresponding tariff shock $\Delta t_{p'}^{Trump}$ is treated in the same way and counted into the Trump-tariff exposure $TrumpTariffExpo_c$. In essence, $L_{c,p}/L_p$ addresses differential ubiquity of product p's production across counties, so that a tariff-ridden product whose production is more concentrated in a county brings the county a heavier tariff shock.

Because county-product level employment data are nonexistent, we approximate $L_{c,p}/L_p$ with its county-industry level employment counterpart $L_{c,j}/L_j$. Such an approximation has been extensively used in the recent literature on how import competition influences local labor markets (e.g., Autor et al., 2013; Acemoglu et al., 2016; Pierce and Schott, 2020).[3] The merging of HS-level data and NAICS-level County Business Patterns (CBP), as a standard practice in the literature, has an adequate precision. Pierce and Schott (2012) provide a detailed concordance between HS codes and SIC codes, while Autor et al. (2013) provide a weighted crosswalk between SIC codes in the Pierce-Schott concordance and the NAICS codes in the CBP data.

The upper panel of Figure 1 shows the geographical distribution of the tariff exposure we constructed. 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 our instrumental strategy and 2SLS results in Section 3.2. 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):

$$R_{c,2018} - R_{c,2016} = \alpha_0 + \alpha_1 TrumpTariffExpo_c + \mathbf{X}_c \bar{\beta} + \gamma_{s(c)} + \varepsilon_c, \tag{2}$$

where the dependent variable is the change in the Republican vote share R_c of county c between the house elections of 2018 and the house elections of 2016.[4] $TrumpTariffExpo_c$ 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 for the relative importance of counties in determining the election outcome (alternative weights will be used as a robustness check).

The results from regression specification (2) are reported in Panel A of Table 2, showing that 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 0.69 percentage point increase in the Republican vote share (that is, $0.007 \times 97.91 \approx 0.685$). 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 that voted for Demo-

[3] See Autor, Dorn, and Hanson (2016) for a review of this literature.

[4] As noted in Section 2.2, county c is one single county (county-district duplet) if it corresponds to one district (multiple districts).

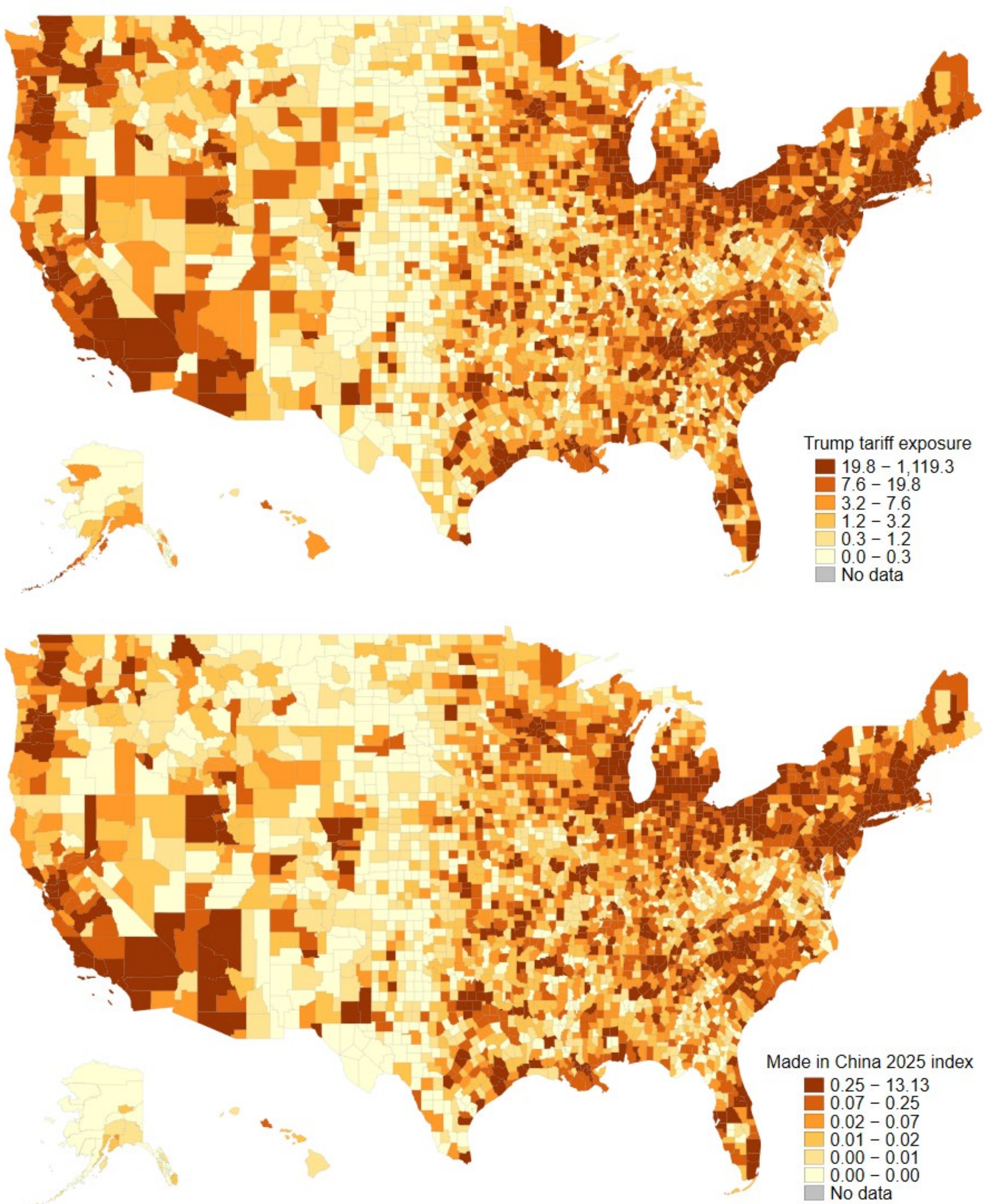

Figure 1:

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 Statistics

	(1) Obs.	(2) Mean	(3) S.D.	(4) Min	(5) Max
Panel A: Election-related variables†					
Republican vote share 2018	3758	0.59	0.20	0	1
Republican vote share 2016	3755	0.63	0.22	0	1
Panel B: Exposure to Trump's China tariffs					
Trump tariff exposure§	3758	28.56	97.91	0	1119.34
MIC2025¥	3758	0.43	1.41	0	13.13
Panel C: County characteristics£					
Manufacturing share (%)	3758	30.62	13.14	2.72	139.98
Median wage (log)	3758	10.82	0.26	9.87	11.77
Labor participation rate (%)	3758	59.45	7.91	11.60	84.40
Unemployment rate (%)	3758	6.41	2.90	0	28.8
Population (log)	3758	10.69	1.78	4.30	16.13
High school (%)	3758	32.32	8.01	6.70	56.57
College degree (%)	3758	32.28	5.69	8.53	50.51
Bachelor degree or higher (%)	3758	23.55	10.79	3.98	79.55
Black (%)	3758	7.59	11.25	0	69.21
Asian (%)	3758	1.61	3.15	0	37.62
Hispanic (%)	3758	7.30	10.58	0	70.53
Male (%)	3758	50.65	3.25	39.62	92.11
Age 16-29 (%)	3758	17.66	4.11	2.93	59.61
Age 30-54 (%)	3758	31.08	3.00	10.98	46.92
Age 55-74 (%)	3758	23.86	4.44	6.50	62.16
Evangelical protestant adherents (%)	3703	38.18	22.68	0	100
Mainline protestant adherents (%)	3703	30.14	17.88	0	100
Black protestant adherents (%)	3703	2.55	5.25	0	53.19
Catholic adherents (%)	3703	23.36	21.41	0	100
Orthodox adherents (%)	3703	0.34	2.54	0	87.09
Female candidate (0 or 1)	3758	0.41	0.49	0	1
Population density (people per square kilometer)	3758	229.05	1279.34	0.01	27819.8
Gini coefficient	3758	0.45	0.04	0.33	0.6
Trade shock	3758	2.76	2.68	-0.63	43.08

Each observation is a county-district duplet. Panel A relates to dependent variables in our analysis, obtained from Dave Leip Atlas. Panel B relates to the main explanatory variable and the 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 3.2.

£ See Appendix A.1 for sources.

cratic presidential candidates (i.e., "blue states" in column (3)) between 1992 and 2012.[5] The results

[5]Since Trump won several previously blue states in 2016, we do not use the 2016 presidential election results to designate

Table 2: The OLS Results

	(1)	(2)	(3)	(4)	(5)
Dep. variable:	Difference in the Republican vote share (2018 minus 2016)				
Panel A: Baseline Results					
Sample:	All	Red	Blue	Republican incumbent	Democratic incumbent
Trump tariff exposure	0.007***	0.008***	0.003	0.005***	0.008**
	(0.002)	(0.002)	(0.003)	(0.001)	(0.003)
Manufacturing share	-0.054	-0.102*	-0.090**	-0.024	-0.113**
	(0.032)	(0.056)	(0.039)	(0.045)	(0.050)
Median wage (log)	7.182	-16.401	-10.483	7.351	-3.868
	(7.374)	(9.464)	(13.142)	(7.161)	(12.284)
Labor participation rate	-0.206*	-0.063	-0.099	-0.145	0.032
	(0.119)	(0.212)	(0.390)	(0.154)	(0.271)
Unemployment rate	0.750**	-0.082	-0.699	0.620**	0.691
	(0.345)	(0.336)	(0.923)	(0.295)	(0.672)
Population (log)	-0.848	-0.952	0.931	-1.092	-1.205
	(0.936)	(0.833)	(1.549)	(0.656)	(1.510)
Education-related controls	Yes	Yes	Yes	Yes	Yes
Ethnicity-related controls	Yes	Yes	Yes	Yes	Yes
Age-related controls	Yes	Yes	Yes	Yes	Yes
Religion-related controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	3700	1047	724	2888	811
Adjusted R-squared	0.262	0.274	0.412	0.247	0.323
Panel B: Robustness Checks					
Specification:§	Without exempted products	Binary tariffs	Alternative exposure formula	Alternative weights	
Trump tariff exposure	0.007***	0.081***	0.007***	0.007***	
	(0.002)	(0.022)	(0.002)	(0.002)	
Control variables	Yes	Yes	Yes	Yes	
State FE	Yes	Yes	Yes	Yes	
Observations	3700	3700	3700	3700	
Adjusted R-squared	0.262	0.261	0.261	0.279	

This table presents our OLS results. Panel A: Column (1) uses the full sample, where sample size 3,700 refers to all county-district duplets with nonmissing depndent and explanatory variables. Columns (2) and (3) limit the sample to the observations 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 observations having incumbents from one single party. Panel B: § See Section 3.1 for the details of each check (regression specifications are otherwise the same as in column (1) of Panel A). Both Panels: Full results are reported in the appendix. Robust errors are clustered at the state level.* p<0.10, ** p<0.05, *** p<0.010.

in these two columns are similar to those in column (1), except that the blue-state result is statistically insignificant.[6] We also run the regression for congressional districts with Republican and Democratic

blue states. Nonetheless, with those blue states designated as blue states as well, our main findings remain the same (available upon request).

[6]The subsample sizes in columns (2) and (3) do not add up to the sample size in column (1) because many states (such as

incumbents separately, and the results remain similar to those in column (1).[7, 8]

In Panel B of Table 2, we report four robustness checks on the findings from Panel A. In column (1), we exclude the products that were later exempted from the China tariffs. There exist a small number of products exempted from Tranches 2 and 3 when the two lists took effect.[9] In column (2), 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. In column (3), we use an alternative exposure measure:

$$TrumpTariffExpo'_c = \sum_{p \in c} \frac{L_{c,p}}{L_c} \Delta t_p^{Trump}, \tag{3}$$

where the weights normalize the employment weights associated with each county. Unlike exposure measure (1) that stipulates the sum of employment shares to be one for each product p (i.e., $\sum_c \frac{L_{c,p}}{L_p} = 1$), the alternative exposure measure (3) stipulates the sum of employment shares to be one for each county c (i.e., $\sum_p \frac{L_{c,p}}{L_c} = 1$).[10] The two measures differ in viewing which entity, cross-county employment related to one tariff-ridden product or within-county employment related to multiple tariff-ridden products, absorbs the full shock imposed by the tariff shocks. We think a tariff is, above all, a product-level policy and thus take the former view. Namely, we consider cross-county employment related to one tariff-ridden product as the full shock absorber, and elect to use exposure measure (1) as our main measure. The latter view, which informs exposure measure (3), is justifiable as well, but less attractive in our context because Trump's tariffs across products are sparse such that a large number of counties would have zero exposure under exposure measure (3). We use exposure measure (3) only as a robustness check. In column (4), we use county-level population instead of voter number to weight the regression. Arguably, population size reflects certain aspects of local political influence that voter number does not capture. As shown, all these columns deliver results that resemble those in Panel A.

swing states) are neither red nor blue.

[7]The sample-size ratio between columns (4) and (5) is 2,888:811 (approximately 3.56:1), which is greater than the house seat ratio 241:194 (approximately 1.2:1), because counties having multiple districts are treated as separate observations. The Republican incumbencies are magnified by their relative prevalence in rural areas. Since population density is lower in rural areas than in urban areas, districts in rural areas, which are apportioned according to population in the same manner as those in urban areas, span more counties than those in urban areas.

[8]The sum of the two subsamples (2,888+811=3,699) is one observation fewer than the sample size in column (1), because Jefferson County, Kentucky (Kentucky District 3) is the only county-district with a Democratic incumbent in the state. As a singleton, it is excluded by the regression since state fixed effects are used.

[9]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.

[10]As before, $L_{c,p}/L_c$ is approximated by its county-industry level employment counterpart $L_{c,j}/L_c$.

3.2 2SLS Results

3.2.1 Instrumental Strategy

The positive association between county-level tariff exposure and support for Republicans, as shown in Table 2, does not necessarily imply a causal effect of the former on the latter. The Trump administration has an incentive to apply additional tariffs to Chinese products that compete with US products produced in counties with more pro-Republican voters. To address the potential endogeneity, we devise an instrumental strategy based on Chinese State Council's Made-in-China 2025 Initiative (hereafter, MIC2025). The initiative was released in 2015 to guide domestic investments, aiming to improve "industrially relevant technologies" with which China can produce more high value-added products. We manually match the products mentioned in the MIC2025 documents to four-digit product (HS) codes (see Appendix A.2 for details). Our instrumental strategy is informed by the following four characteristics of MIC2025.

First, MIC2025 directly motivated Trump's China tariffs, as made clear by the Trump administration when it launched the China tariffs:[11]

> *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 presidential directive was then faithfully executed by the USTR. As the USTR noted in its announcement of Tranche 1 tariffs (see the first document listed in Section 2.1), "USTR and the interagency Section 301 Committee have carefully reviewed the extent to which the tariff subheadings [...] include products containing industrially significant technology, including technologies and products related to the 'Made in China 2025' program." This close association between MIC2025 and Trump's China tariffs is the foundation of our instrumental strategy, and has been confirmed by our statistical analysis (discussed later).

Second, MIC2025 emphasizes industrially significant technologies, which should not be equated to high-tech sectors. Although the initiative emphasizes several commonly regarded high-tech products (for instance, HS product sectors 84 to 85, machinery and mechanical appliances, and product sectors 86-88, transport equipment), its product coverage is not limited to high-tech sectors. For example, carbon fibers fall under HS code 6815 ("stone or of other mineral substances"), but the HS product sector 68 ("stone, plaster, cement, asbestos, mica or similar materials") is not a high-tech sector. For another example, special synthetic rubber falls under HS code 4002, which as part of HS product sector 40 ("rubber") is rarely considered as high-tech. Likewise, glass substrate used in making LED glass

[11] See *Statement on Steps to Protect Domestic Technology and Intellectual Property from China's Discriminatory and Burdensome Trade Practices* (29 May 2018). The statement is downloadable at https://trumpwhitehouse.archives.gov/briefings-statements/statement-steps-protect-domestic-technology-intellectual-property-chinas-discriminatory-burdensome-trade-practices/.

is categorized under HS product sector 70 ("glass and glassware"), a conventional technology sector. Since every sector in the industrial world has its advanced technologies that distinguish its innovative products from others, the variations generated by MIC2025 capture industrial significance beyond differences between high-tech and non-high-tech sectors.

Third, on the China side, MIC2025 is not an industrial policy but a concept coined by the State Council to imitate counterpart concepts promoted by industrialized countries (e.g., "Industrie 4.0" of Germany). MIC2025 proposes nothing concrete: neither implementable policies nor binding commitments. The goals specified in the initiative are ambiguous and lacking in details.[12] In fact, the initiative falls short of an authoritative guideline by the standard of Chinese politics. Published as a State Council document (#2015-28), it was mentioned only once by the State Council's head (Premier Li Keqiang) to the People's Congress as a hand-waving effort, and never appeared again in the national political arena of China.[13] Conceivably, it would not have received as much attention as it did had it not become a point of contention during the US-China trade war. The USTR noted in its *2016 Report to Congress on China's WTO Compliance* that China has a wide array of "problematic industrial policies," among which MIC2025 is merely a long-term plan with goals about which industry experts are skeptical.[14] MIC2025 played down the use of strategic maneuvers, in comparison with industrial policy narratives used by China in the past. The USTR actually noted that MIC2025 "represents a modest improvement over strategic plans [China] rolled out since 2010" (ibid., page 15).

Fourth, on the US side, the Trump administration targeted its China tariffs at MIC2025 as a precautionary measure to deter China's industrial ambitions. As MIC2025 is a long shot that has yet to be developed into industrial or trade policies, the initiative is expected to have no impact on US house election results at the county level except through Trump's precautionary tariffs. The comparative advantage of producing MIC2025 products—such as the aforementioned machinery and transport equipment—remains on the US side rather than the China side. By targeting those products, the Trump administration sought to reduce US imports of them from China, thereby curtailing China's related production capacity, intellectual property exploitation, and supply network growth. To this end, Trump's tariffs also reduced bilateral foreign direct investment (FDI) related to those products between the two countries, because multinational production generally needs constant bilateral exporting and importing of intermediate inputs and final products.[15] In essence, Trump's China tariffs are product-level

[12]The term goals specified in the initiative include "By 2025: Boost manufacturing quality, innovation, and labor productivity; obtain an advanced level of technology integration; reduce energy and resource consumption; and develop globally competitive firms and industrial centers. By 2035: Reach parity with global industry at intermediate levels, improve innovation, make major breakthroughs, lead innovation in specific industries, and set global standards. By 2049: Lead global manufacturing and innovation with a competitive position in advanced technology and industrial systems" (translation by the U.S. Congressional Research Service (2020)).

[13]MIC2025 is in no way comparable with China's Five-Year Plans, a policy legacy inherited from the Soviet Union which is regularly drafted by the Central Committee of the Communist Party of China and reviewed and approved by the People's Congress.

[14]The report is downloadable at https://ustr.gov/sites/default/files/2016-China-Report-to-Congress.pdf.

[15]Because of the need for trading intermediate inputs and final products, FDI is known to be vulnerable to bilateral tariffs (see Díez (2014) and Antràs and Yeaple (2014) among others). The relevance of tariffs to FDI has a nontrivial implication on

decoupling policies aiming to turn off various economic interests between the two countries, including but not limited to direct exporting.

Among the above four characteristics of MIC2025, the latter three inform the exclusion condition of a valid instrumental variable. The exclusion condition itself is not directly testable, whereas we will conduct a variety of checks to ascertain whether the impact of MIC2025 on the midterm elections bypasses the tariff channel. The first characteristic above informs the relevance condition of a valid instrumental variable. The relevance condition is directly testable. In Table 3, Trump's China tariff lists and rates are regressed on whether an import product code relates to MIC2025. In Panel A, each observation relates to one four-digit product (HS) code. The independent variable $MIC2025_p$ is an indicator constructed for each four-digit product code. The dependent variable is either a China tariffs indicator that equals 1 if any six-digit product under the four-digit product is levied with the new tariffs, or the average of the new tariffs across six-digit products under the four-digit product. In Panel B, each observation is a six-digit product code and $MIC2025_p$ remains at the four-digit level. The dependent variable is either a China tariffs indicator that equals 1 if any product under the six-digit product is levied with the new tariffs or the average of the new tariffs across products under the six-digit code. The use of different levels of aggregation in the two panels aims to avoid aggregation-induced spurious correlation. We include two-digit product fixed effects in all regressions. As shown, there is a strong association between Trump's China tariffs and China's MIC2025 products. We also experiment with excluding the products later exempted from China tariffs. 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 3.2 to 3.7 percentage points.

We construct our instrumental variable at the county level by aggregating MIC2025-related products to the county level:

$$MIC2025_c = \sum_{p \in c} \frac{L_{c,p}}{L_p} MIC2025_p, \tag{4}$$

where $MIC2025_p$ is the four-digit MIC2025 indicator mentioned above. As before, $L_{c,p}/L_c$ is approximated by its county-industry level employment counterpart $L_{c,j}/L_c$. 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.

3.2.2 2SLS Findings

By instrumenting the tariff exposure with $MIC2025_c$, we conduct 2SLS estimation and report the results in Panel A of Table 4. As indicated in column (1), greater exposure to Trump's China tariffs raises local support for Republican house candidates. The magnitude of the coefficient 0.006 is close to its

our instrumental strategy: FDI, as a nontrade channel for influencing local voters, does not bypass but works through local tariff exposure. Consider a county expecting inbound FDI from China related to a MIC2025 product. The FDI project is now likely to fail because Trump's China tariffs render the inputs or outputs more costly to trade between the two countries.

Table 3: 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			Applied Trump's China tariffs (without exemptions)		
	Indicator I (=1 if applied)		New tariff rate (Percentage points)	Indicator I (=1 if applied)		New tariff rate (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	1160	1160	1160	1130	1130	1130
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	4589	4589	4589	4483	4483	4483
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). Columns (1) and (2) use an indicator variable (equal to 1 if Trump's China tariffs are applied to any of the products under the four-digit product code) as the dependent variable, and column (3) uses the average tariff rates as the dependent variable. Column (1) uses a linear probability model, column (2) uses a probit model, and column (3) uses an ordinary 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.

OLS counterpart 0.007 in Table 2. The two coefficients are within one standard error of each other. The finding applies to both red-state and blue-state subsamples in columns (2) and (3), respectively. The coefficient of tariff exposure in column (4) here loses the statistical significance that it has in Table 2, indicating that its OLS estimate overstates the effect of tariff exposure on Republican vote share in Republican-incumbent counties. The coefficient of tariff exposure in column (5) here maintains the statistical significance that it has in Table 2. Following the structure of Panel B of Table 2, we conduct robustness checks on the 2SLS estimation and report them in Panel B of Table 4. The findings remain robust.[16]

The OLS and 2SLS results, taken together, illustrate that the stance on free trade held by Trump, which is different from the stance of his party, helped the party in the midterm elections of 2018. His protectionist policy did not alienate Republican-leaning voters and might have attracted some Democratic-leaning voters, as the Democratic Party is known to be skeptical of trade liberalization

[16]We also examined, using both OLS and 2SLS, whether the same regression specifications can explain voter turnout. The results are reported in Table A4. Tariff exposure has little explanatory power for voter turnout.

Table 4: The 2SLS Results

	(1)	(2)	(3)	(4)	(5)
Panel A: Baseline Results					
Sample	All	Red	Blue	Republican incumbent	Democratic incumbent
The second stage					
Dep. variable is differenced republican vote share					
Trump tariff exposure	0.006***	0.009***	0.007***	0.003	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Control variables	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	3700	1047	724	2888	811
Adjusted R-squared	0.101	0.243	0.288	0.081	0.176
The first stage					
Dep. variable is Trump tariff exposure					
MIC2025	77.206***	67.912***	80.611***	73.680***	74.116***
	(3.561)	(0.334)	(4.221)	(6.099)	(2.601)
Panel B: Robustness Checks					
Specification:§	Without exempted products	Binary tariffs	Alternative exposure formula	Alternative weights	
The second stage					
Dep. variable is differenced republican vote share					
Trump tariff exposure	0.006***	0.076***	0.006***	0.007***	
	(0.002)	(0.025)	(0.002)	(0.002)	
Control variables	Yes	Yes	Yes	Yes	
State FE	Yes	Yes	Yes	Yes	
Observations	3700	3700	3700	3700	
Adjusted R-squared	0.102	0.101	0.101	0.106	
The first stage					
Dep. variable is Trump tariff exposure					
MIC2025	74.661***	6.155***	76.931***	77.442***	
	(3.820)	(0.269)	(3.573)	(3.510)	

This table presents our 2SLS results. Panel A: Column (1) uses the full sample, where the sample size 3,700 refers to all county-district duplets with nonmissing depndent and explanatory variables. Columns (2) and (3) limit the sample to the observations 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 observations having incumbents from one single party. Panel B: § See Section 3.2 for the details of each check (regression specifications are otherwise the same as in column (1) of Panel A). Both Panels: Full results are reported in the appendix. Robust errors are clustered at the state level. *** p<0.010.

(see Che et al. (2016) and Conconi et al. (2019) among others). To this end, we take a further look into the Democratic incumbent subsample in column (5), Panel A of Table 4 by examining whether ethnicity plays a role. Recent studies document welfare deterioration and pro-Republican tendency of White Americans caused by trade liberalization (e.g., Pierce and Schott, 2020; Autor et al., 2020). Hence we hypothesize that the White ethnic group in Democratic-incumbent counties tend to support Republicans because of Trump's trade policy change, all else held equal. We construct a dummy variable $\mathbb{D}(Q(PopShare_c^k) > q)$ for each ethnicity k. $PopShare_c^k$ is the population share of ethnicity k in county c, which is converted to a percentile by $Q(\cdot)$. The greater q is, the larger ethnicity-k concentration $\mathbb{D}(Q(PopShare_c^k) > q)$ indicates. By design, the information conveyed by the dummy variable decreases with q. For instance, $PopShare_c^k > 0.10$ is far less informative than $PopShare_c^k > 0.90$ in characterizing the size of ethnicity group k in county c. We design the dummy in such a way that q-value increments can illustrate an increasingly revealing pattern.

Among the four ethnicity groups (White, Black, Hispanic, and Asian) in our data, we choose Asian as the reference group, because Asians have the smallest population share across the US and meanwhile China is an Asian country. We insert $\mathbb{D}(Q(PopShare_c^{White}) > q)$, $\mathbb{D}(Q(PopShare_c^{Black}) > q)$, $\mathbb{D}(Q(PopShare_c^{Hispanic}) > q)$, and their interactions with $TrumpTariffExpo_c$ into the specification of column (5), Panel A of Table 4. The results are reported in Table 5. As shown, as q rises from 0.10 to 0.90, the coefficient of the interaction terms turns from negative to positive for Whites, whereas from positive to negative for Hispanics. The change for Blacks is not monotonic. Only the interaction between $\mathbb{D}(Q(PopShare_c^{White}) > 0.75)$ and $TrumpTariffExpo_c$ is statistically significant. In addition, the coefficient of the uninteracted $TrumpTariffExpo_c$ is insignificantly negative across the board, and the coefficient of the uninteracted $\mathbb{D}(Q(PopShare_c^{White}) > 0.75)$ is significantly negative. Notice that these findings rest on a small subsample and thus have limited power. When q rises from 0.75 to 0.90, the statistical significance disappears, which is likely driven by the further reduced variation in $\mathbb{D}(Q(PopShare_c^{White}) > q)$ when q keeps increasing.[17] Taken together, these ethnicity patterns are consistent with both the skeptical view of Democrats on free trade and the interplay between White ethnicity and trade liberalization in recent US elections documented in the literature.

We next conduct Rotemberg decomposition for our 2SLS estimation. Goldsmith-Pinkham, Sorkin, and Swift (2020) (hereafter, GSS) developed an econometric method to explicate the variations used by Bartik instruments such as ours. The method decomposes a 2SLS estimator into a sum of product-specific parameters: $\hat{\beta} = \sum_p \hat{\alpha}_p \hat{\beta}_p$, where $\hat{\alpha}_p$ represents the relative importance of product p when the instrument is used in estimation.[18] The decomposition is known as Rotemberg decomposition, and $\hat{\alpha}_p$ as Rotemberg weights. Since each product has its own shock (denoted by g_p) and accounts for an amount of employment at location c (denoted by $z_{c,p}$), products have differing importance to a given Bartik-instrument estimation, represented by Rotemberg weights $\{\hat{\alpha}_p\}_p$. Using the computer program provided by GSS, we estimate the Rotemberg weights and summarize them in Table 6.

Table 6 follows the format used by GSS to exemplify their methods with Autor-Dorn and Card data. The upper panel demonstrates that the Rotemberg weights in our case correlate with both product-

[17] Also in line with this reasoning, the statistical significance of the uninteracted $\mathbb{D}(Q(PopShare_c^{White}) > q)$ decreases when q rises from 0.75 to 0.90.

[18] The p in GSS represents an industry. $\hat{\alpha}_p$ is a weight rather than a share because the Rotemberg decomposition does not require $\sum_p \hat{\alpha}_p = 1$. The computer program provided by GSS is publicly available at https://github.com/paulgp/bartik-weight.

Table 5: A Closer Examination of Column (5), Panel A of Table 4

	(1)	(2)	(3)	(4)
Dep. variable:	Difference in the Republican vote share			
Trump tariff exposure	-0.168	-0.033	-0.043	-0.189
	(0.234)	(0.102)	(0.036)	(0.166)
Trump tariff exposure X	-0.003			
Dummy (White population share, percentile > 10th)	(0.005)			
Trump tariff exposure X	0.074			
Dummy (Black population share, percentile > 10th)	(0.175)			
Trump tariff exposure X	0.105			
Dummy (Hispanic population share, percentile > 10th)	(0.150)			
Dummy (White population share, percentile > 10th)	-1.562			
	(3.235)			
Dummy (Black population share, percentile > 10th)	-2.428			
	(3.222)			
Dummy (Hispanic population share, percentile > 10th)	-2.676			
	(3.613)			
Trump tariff exposure X		-0.009		
Dummy (White population share, percentile > 25th)		(0.010)		
Trump tariff exposure X		-0.055		
Dummy (Black population share, percentile > 25th)		(0.085)		
Trump tariff exposure X		0.104		
Dummy (Hispanic population share, percentile > 25th)		(0.073)		
Dummy (White population share, percentile > 25th)		1.639		
		(1.984)		
Dummy (Black population share, percentile > 25th)		1.955		
		(2.743)		
Dummy (Hispanic population share, percentile > 25th)		-6.475		
		(4.668)		
Trump tariff exposure X			0.065***	
Dummy (White population share, percentile > 75th)			(0.023)	
Trump tariff exposure X			0.008	
Dummy (Black population share, percentile > 75th)			(0.008)	
Trump tariff exposure X			-0.015	
Dummy (Hispanic population share, percentile > 75th)			(0.027)	
Dummy (White population share, percentile > 75th)			-7.159**	
			(3.211)	
Dummy (Black population share, percentile > 75th)			0.521	
			(3.097)	
Dummy (Hispanic population share, percentile > 75th)			-2.972	
			(2.702)	
Trump tariff exposure X				0.202
Dummy (White population share, percentile > 90th)				(0.165)
Trump tariff exposure X				0.004
Dummy (Black population share, percentile > 90th)				(0.069)
Trump tariff exposure X				-0.008
Dummy (Hispanic population share, percentile > 90th)				(0.007)
Dummy (White population share, percentile > 90th)				-8.735*
				(5.133)
Dummy (Black population share, percentile > 90th)				4.678
				(3.450)
Dummy (Hispanic population share, percentile > 90th)				3.953*
				(2.305)
Observations	811	811	811	811
Adjusted R-squared	0.170	0.189	0.201	0.182

This table continues to present 2SLS results from the sample of column (5), Panel A of Table 4. For each ethnic group among White, Black, and Hispanic, a dummy variable is created representing the population share of the ethnicity is above the x-th percentile across counties, x=10th, 25th, 75th, or 90th. From column (1) to (4) in the table, x rises so that the dummy variables indicate a larger concentration of the ethnicity in focus. These dummy variables are inserted into regressions uninteracted and interacted with Trump tariff exposure. Asian ethnic group is the reference group. All other specifications remain the same as those of column (5), Panel A of Table 4. Robust errors are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.010.

specific shocks g_p and county-product specific employment weights $z_{c,p}$. The lower panel presents the five products with the largest Rotemberg weights. As noted by GSS, examining such top products helps expose influential products and industries in a Bartik-instrument estimation (e.g., oil and gas

Table 6: Rotemberg Decomposition of the 2SLS Results

Correlations

	α	g	*var(z)*
α	1		
g	-0.439	1	
var(z)	0.713	-0.349	1

Products with top-five Rotemberg weights

	α
Glass and glassware	0.056
Arms and ammunition; parts and accessories thereof	0.046
Fertilisers	0.046
Vegetable plaiting materials; vegetable products n.e.s.	0.043
Iron and steel	0.042

This table reports Rotemberg decomposition of the results in column (1), Panel A of Table 4. See Section 3.2.2 of the text for details. The format of the table follows Goldsmith-Pinkham, Sorkin, and Swift (2020).

extraction and automobile in Autor and Dorn (2013)). In our case, the top products have similar weights and none of them display considerable influences.[19] In fact, some of those products are not in the spotlight of the trade war, as the relative importance of industries in a Bartik-instrument estimation depends not on shocks alone but on the interaction between shocks and shares.

The Rotemberg decomposition serves as a check on our instrumental strategy. The 2SLS estimates reported in this section survive a long list of other identification and robustness checks. The results from additional checks are reported in the next section.

4 Additional Identification and Robustness Checks

4.1 Sector Heterogeneity

A potential concern over our instrumental variable $MIC2025_p$ is sector heterogeneity. The aforementioned Rotemberg decomposition shows that our instrumental strategy is not driven by influential products. As an alternative check, we regress $MIC2025_p$, namely whether product p relates to MIC2025, on two-digit HS code (product sector) dummies $\mathbb{I}_{p2}$ and use the residuals to construct an instrumental variable $MIC2025^e_c$ through the previous Bartik formula (4). This auxiliary regression is

[19] Whether having influential products or industries is not an indicator of estimation success. Goldsmith-Pinkham et al. (2020) give two examples, one (Autor-Dorn) with influential groups and the other (Card) without.

a linear probability model that captures the differing relevance of MIC2025 across sectors. The variations not explained by sector dummies, namely the regression residuals, are product-specific deviations from sector-average MIC2025 relevance. Resting on such "sector-free" MIC2025 relevance, the newly constructed instrumental variable $MIC2025_c^e$ (hereafter, auxiliary instrumental variable) is, by design, insensitive to cross-sector differences in the propensity of being selected into MIC2025.

The 2SLS results from using the auxiliary instrumental variable are reported in Table 7. They resemble those in Table 4, except that the first-stage coefficients become smaller in magnitude (remaining statistically significant). Given the high similarity between Tables 4 and 7, we prefer the original instrumental variable because its results are easier to interpret. In addition, MIC2025, as a government initiative, has its own logic of design such that the original variable reflects more truthfully the variation at play.[20] Thus, using the original $MIC2025_c$ is a relatively safe approach.

Table 7: Auxiliary 2SLS Results

	(1)	(2)	(3)	(4)	(5)
Sample	All	Red	Blue	Republican incumbent	Democratic incumbent
The second stage					
Dep. variable is differenced republican vote share					
Trump tariff exposure	0.007***	0.008***	0.000	0.006	0.007***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.001)
Control variables	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	3700	1047	724	2888	811
Adjusted R-squared	0.101	0.243	0.291	0.084	0.176
The first stage					
Dep. variable is Trump tariff exposure					
MIC2025 auxiliary regression residuals	4.193***	7.889***	3.903***	4.406***	4.123***
	(0.200)	(0.029)	(0.057)	(0.437)	(0.117)

This table presents our 2SLS results from using residuals of auxiliary regressions as instrumental variable. Column (1) uses the full sample, where the sample size 3,700 refers to all county-district duplets with nonmissing depndent and explanatory variables. Columns (2) and (3) limit the sample to the observations 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 observations having incumbents from one single party. Robust errors are clustered at the state level. *** p<0.010.

Another type of possible sector heterogeneity lies on the US side. Anecdotes claim that the Trump administration favors traditional industrial sectors and disfavors high-tech sectors (see for example, Brownstein (2017), Karsten (2017), and Gayer (2020)). To our knowledge, there has not been rigor-

[20]As discussed in Section 3.2.1, an important characteristic of MIC2025 is its emphasis on industrially significant technologies, which are not necessarily originated or operated in commonly regarded high-tech sectors. Therefore, the auxiliary regression approach risks overstating (understating) the MIC2025 relevance of products in sectors less (more) represented in MIC2025.

ous empirical evidence corroborating this claim. However, Trump's H-1B reform is heavily criticized by high-tech sectors, while his tax reforms appear to benefit traditional industrial sectors more than others.[21] In Appendix A.3, we examine whether the two reforms explain our previous findings. The results from high and low influenced groups of both reforms lead to similar findings as before. Thus, the previous findings should not be attributed to these contemporary policy changes.

4.2 External Validation: MIC2025 in US and China's Trade Statistics

We employ external data to check whether MIC2025 had already affected American voters economically by the time of Trump's China tariffs and the midterm elections. We merge our MIC2025 product list with product-level trade data of the two countries. The data used here cover a nine-year period, from the year 2010 to the midterm-election year 2018. If MIC2025 had influenced the U.S. economy before Trump's China tariffs, we should be able to detect the influences in the US trade data—or at least in China's trade data—during this period, especially after the MIC2025 release year 2015.

In Panel A of Figure 2, we first plot US imports from the rest of the world (the top-left graph) and US exports to the rest of the world (the bottom-left graph) over time. The dashed lines in the two graphs correspond to MIC2025-related products. MIC2025-related products consumed and produced by the US appear to be quite stable in the few years around 2015. The stability is particularly salient when the dashed lines are compared with the solid lines that represent all-product trade (either imports or exports) of the US. Then we examine US trade with China in the same fashion and reach similar time trends, as displayed in the top-right and bottom-right graphs of Panel A. The lack of change around the year 2015 indicates that the US neither imported more nor exported less MIC2025-related products after China released MIC2025.

Correspondingly, data on the China side show no change in the MIC2025-related trade of China. Panel B of Figure 2 follows the same structure as Panel A, except having US imports or exports replaced by China's imports or exports. As shown, China neither exported more nor imported less MIC2025-related products, a finding that applies to both China's trade with the US and with the rest of the world.

In addition to graphical analysis, we specify the following regression to examine the two countries' imports and exports of MIC2025-related products:

$$\ln T_{pt} = \mu + \omega MIC2025_p \times \mathbb{I}(t \geq 2015) + \lambda_{p4} + \lambda_t + \epsilon_{pt}, \tag{5}$$

where T_{pt} is trade volume (either imports or exports) of product p of either country in year t. The indicator variable $\mathbb{I}(t \geq 2015)$ captures the presence of MIC2025, and our parameter of interest is ω. Each observation is associated with a six-digit product p in year t, while $MIC2025_p$ remains at the four-digit product level as before. A constant term μ, a four-digit product fixed effect λ_{p4}, and a year

[21] Lake and Nie (2021) find that Trump's policies rather than polarization are the main reason for Trump's defeat in the presidential election of 2020.

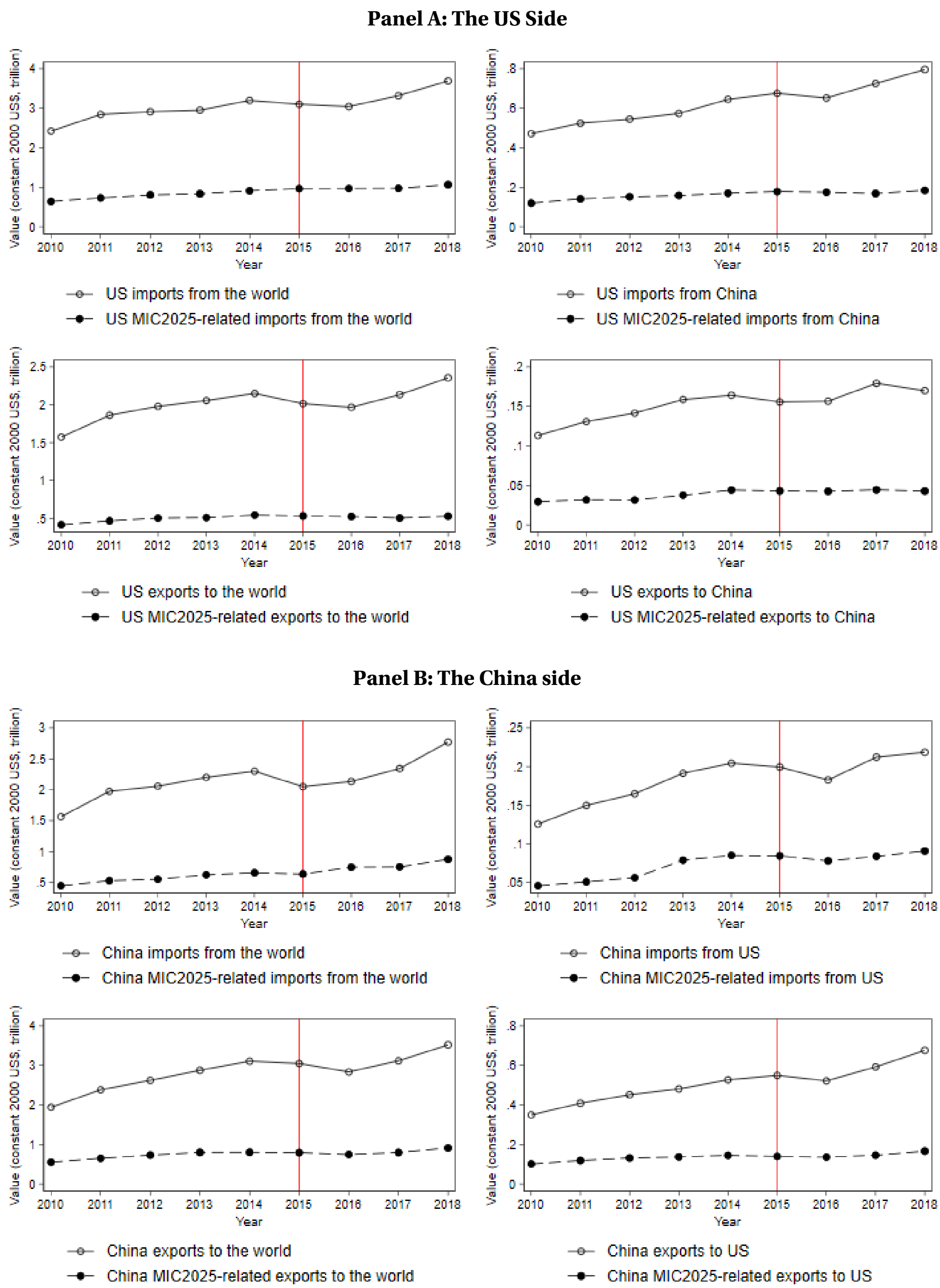

Figure 2: Unilateral and Bilateral Trade of MIC2025-related Products

In Panel A (respectively, Panel B), the trends in the US (China's) imports and exports of products related to China's MIC2025 are plotted across years. 2015 (marked) is the year when MIC2025 was released by the Chinese State Council.

fixed effect λ_t are included in the regression. The results are reported in Panel A of Table 8, for the

Table 8: US and China's Exports and Imports of MIC2025-related Products

	(1)	(2)	(3)	(4)
Panel A: The US side				
	From/to the world		From/to China	
Dep. variable	ln(Imports)	ln(Exports)	ln(Imports)	ln(Exports)
MIC2025 × After-2015 dummy	0.014	-0.008	0.167	-0.090
	(0.045)	(0.017)	(0.187)	(0.203)
Observations	10984	10984	10750	10750
Adjusted R-squared	0.955	0.958	0.895	0.800
4-digit HS product FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Panel B: The China side				
	From/to the world		From/to China	
Dep. variable	ln(Imports)	ln(Exports)	ln(Imports)	ln(Exports)
MIC2025 × After-2015 dummy	-0.099	-0.006	-0.245	0.235
	(0.130)	(0.060)	(0.218)	(0.155)
Observations	10902	10902	10527	10527
Adjusted R-squared	0.917	0.920	0.868	0.906
4-digit HS product FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Each observation corresponds to one product-year duplet. The data cover the years 2010 to 2018. 2015 is the year when the Chinese State Council released 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 level.

US trade with the rest of the world (columns (1)-(2)) and the US trade with China (columns (3)-(4)).[22] The same analysis is conducted for China and reported in Panel B of the table. Once again, we find no association between MIC2025 and the two countries' trade performance. In sum, trade statistics imply no materialized trade changes generated by MIC2025 by the time of the midterm elections.

4.3 China's Retaliatory Tariffs

In response to Trump's China tariffs, the Ministry of Commerce of China announced retaliatory tariffs. The retaliation potentially influenced US midterm house elections, as the rising support for Republicans we found may result from China's retaliatory tariffs rather than Trump's China tariffs. To delineate the relationship between the two competing explanations, a conceptual framework is needed here.

[22] The difference in sample size between columns (1)–(2) and columns (3)–(4) is small, because most of the six-digit product varieties traded by the two countries with the rest of the world appear in their trade with each other.

Conceptually, our regression specification (2) identifies the sum of two effects:[23]

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

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

Our previous estimates $\hat{\alpha}_1^{OLS}$ and $\hat{\alpha}_1^{2SLS}$ represent a total effect of Trump's China tariffs on the midterm outcome for Republicans. "China's retaliation function" in equation (7) is a response function informing China's retaliatory tariffs. That is, in response to Trump's China tariffs on Chinese product p (i.e., Δt_p^{Trump}), China retaliated by charging an additional tariff $\Delta t_{p'}^{China}$ on US product p'. "Political feedback to China's retaliation" is the political responses of local voters to the Republican Party, given China's retaliatory tariff on the US product p'. The aggregate response of the county is a summation across all products made in the county, namely across p' in the set $\{p' \in c\}$ for each county c. The voters who benefited from Trump's tariffs on Chinese products tended to support Trump's party (i.e., the direct effect), while those who were harmed by China's retaliatory tariffs tended to blame either China or Trump (and thus his party) and vote accordingly (i.e., the indirect effect).

Now we designate pro-Trump (and thus pro-Republican) effects as *positive* effects, and anti-Trump effects as *negative* effects. Under the above framework, the previously estimated positive total effect implies one of the four following possibilities: (i) a positive direct effect and no indirect effect, (ii) a positive indirect effect and no direct effect, (iii) positive direct and indirect effects, or (iv) a positive direct effect and a negative indirect effect, with the former outweighing the latter.

To differentiate the four possibilities above, we exclude all products that are included in China's retaliatory tariffs for each county c. This will turn off the indirect effect: the set $\{p' \in c\}$ in equation (7) is now made empty. As a result, China's retaliation becomes irrelevant to county c, so that the estimation is free from retaliation and the estimated total effect equals the direct effect. Results from the "retaliation-free" experiment are reported in Table 9. Our previous findings still hold. In addition, both the OLS- and 2SLS-coefficients are larger in magnitude than their counterparts in Tables 2 and 4. The results indicate a positive direct effect, countering the possibility (ii) mentioned above. Thus, the sample of products unrelated to China's retaliatory tariffs reproduce our previous findings, supporting a positive direct effect. Therefore, the estimated positive total effect is unlikely to be generated solely by a positive indirect effect.

Two issues should be noted here. First, the products exposed to China's retaliatory tariffs, which are excluded in this empirical experiment, have a large overlap with the products exposed to Trump's

[23]See Appendix A.4 for derivation.

Table 9: Results from a “Retaliation-free” Experiment

	(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	0.037***	0.077*	-0.003	0.030**	0.037
	(0.011)	(0.039)	(0.026)	(0.013)	(0.025)
Control variables	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	3700	1047	724	2888	811
Adjusted R-squared	0.256	0.262	0.410	0.242	0.316
Panel B: 2SLS Results					
Second stage:					
Trump tariff exposure	0.043***	0.101***	0.041**	0.021	0.064***
	(0.012)	(0.029)	(0.014)	(0.016)	(0.020)
Control variables	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	3700	1047	724	2888	811
Adjusted R-squared	0.094	0.229	0.272	0.079	0.163
First stage:					
MIC2025	10.915***	5.831***	13.146***	9.697***	10.665***
	(1.725)	(0.141)	(0.841)	(2.250)	(1.189)

Column (1) uses the full sample. Columns (2) and (3) limit the sample to the observations 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 observations having incumbents from one single party. Control variables are the same as in Tables 2 and 4. Robust errors are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.010.

China tariffs. Therefore, the consistency between previous findings and the findings from Table 9 should not be attributed to plain sample differences. Figure 3 illustrates the overlap between Trump's China tariffs and China's retaliatory tariffs. Each cell in the panel represents 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 (light yellow for 0 and black for the maximum count) in the upper panel. Next, we subtract retaliatory tariffs from the heatmap and display the net counts in the lower panel of the figure. The removal of China's retaliatory tariffs generates a widespread reduction in heat levels but keeps the distribution of heat unchanged. That is to say, there is a heavy overlap between the two countries' trade war tariffs.[24]

[24]For this reason, controlling for county-level exposure to China's retaliation in the original OLS and 2SLS regressions is not a viable option. The two tariff exposure measures would be highly correlated, causing multicollinearity. The multicollinearity

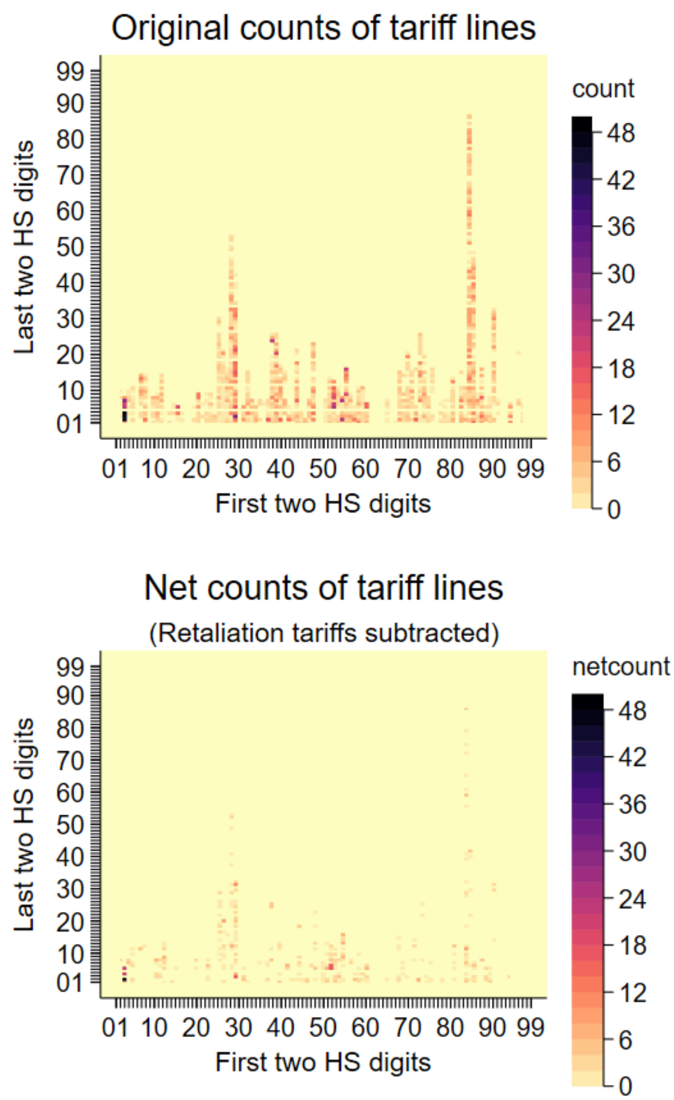

Figure 3: Trump's China Tariffs and China's Retaliatory Tariffs

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.

Second, the indirect effect remains unidentifiable. Our exclusion of retaliatory tariff related products in this empirical experiment removes the indirect effect and thus renders it unidentified. In other

would also be aggravated by the presence of employment weights in both exposure measures.

words, we are unable to tell apart the three remaining possibilities (i), (iii), and (iv). Given the larger OLS and 2SLS coefficients in Table 9 compared to those in Tables 2 and 4, it is tempting to speculate that the indirect effect is negative (i.e., China's retaliation harms Republican candidates). However, we caution against this speculation because the sample used in Table 9 is not the same as the sample used in previous tables, and keep agnostic about whether the indirect effect exists and its direction.

4.4 Congressional District Level Results

Since congressional district (hereafter, district) is the unit of house elections, we also run the previous study at the district level as a robustness check. For this check, county-level data need to be aggregated or disaggregated with population as weights, which inevitably cause inaccuracies. The sample size remarkably shrinks to 435, including 241 Republican-incumbent districts and 194 Democratic-incumbent districts. The district-level results are reported in Table 10. Findings from the full sample are the same as before, albeit less significant statistically. The coefficients of tariff exposure for separate incumbent subsamples are insignificant, though the magnitudes and patterns remain similar as before.[25] In particular, the results from the Democratic-incumbent subsample is relatively more significant in terms of coefficient/standard error ratio.

4.5 Strictly County-level Results

The check in Section 4.4 converts county-district duplets into districts. As a check in the opposite fashion, we now use a strictly county-level sample to rerun the study. As noted earlier, county is the smallest possible unit of nationwide statistics and the unit of vote collection. So, the check we perform here provides a county-level view of the picture. The results are reported in Table 11. Column (1) in the table uses the full sample, representing all counties without missing variables in our sample. A major shortcoming of using a strictly county-level sample is the difficulty in defining incumbents, as counties with multiple districts may have opposing election outcomes across their districts. We count multi-district counties with opposing (respectively, same) party-affiliation incumbents as two separate counties (respectively, one single county), and report the Republican- and Democratic-incumbent subsample results in columns (2)–(3). All these columns produce results similar to those in Tables 2 and 4.

4.6 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 (2) to the previous political cycle 2014-2016. 2014 and 2016 were both election years for the house, and

[25] Incumbencies are determined using the 2016 house election results to avoid vacancies and retain the total sample size 435 (241+194=435).

Table 10: Congressional District Results

	(1)	(2)	(3)
Dep. variable:	Difference in the Republican vote share (2018 minus 2016)		
Sample:	All	Republican incumbent	Democratic incumbent
Panel A: OLS Results			
Trump tariff exposure	0.009**	-0.006	0.009
	(0.004)	(0.007)	(0.007)
Control variables	Yes	Yes	Yes
Observations	435	241	194
Adjusted R-squared	0.033	0.015	0.068
Panel B: 2SLS Results			
Second stage:			
Trump tariff exposure	0.009*	-0.012	0.012
	(0.005)	(0.012)	(0.009)
Control variables	Yes	Yes	Yes
Observations	435	241	194
Adjusted R-squared	0.038	0.010	0.063
First stage:			
MIC2025	0.735***	0.608***	0.754***
	(0.041)	(0.035)	(0.021)

Column (1) uses the full sample. Columns (2) and (3) limit the sample to congressional districts having incumbents from one single party. Robust errors are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.010.

2016 was also the year when Trump was elected president. In this additional robustness check, we replace the dependent variable $R_{c,2018} - R_{c,2016}$ in regression specification (2) with $R_{c,2016} - R_{c,2014}$, and keep the rest of the regression specification the same as before.[26]

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 12.[27] The previously significant effects of Trump's China tariffs on the Republican vote shares all disappear. This finding confirms that pre-trends, if they exist, cannot explain our main findings.

[26]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.

[27]Table 12 does not have columns related to Republican and Democratic incumbents because the incumbents in the year 2018 (elected in the year 2016) were not incumbents in the year 2016 (elected in the year 2014).

Table 11: Strictly County-level Results

	(1)	(2)	(3)
Dep. variable:	Difference in the Republican vote share (2018 minus 2016)		
	All	Republican incumbent	Democratic incumbent
Panel A: OLS Results			
Trump tariff exposure	0.006***	0.005***	0.010***
	(0.002)	(0.002)	(0.003)
Control variables	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Observations	3087	2648	614
Adjusted R-squared	0.175	0.185	0.259
Panel B: 2SLS Results			
Second stage:			
Trump tariff exposure	0.005*	0.004	0.009**
	(0.003)	(0.003)	(0.003)
Control variables	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Observations	3087	2648	614
Adjusted R-squared	0.057	0.075	0.122
First stage:			
MIC2025	71.111***	72.485***	71.868***
	(5.402)	(6.030)	(3.015)

Column (1) uses the full strictly county-level sample. Columns (2) and (3) limit the sample to the counties having incumbents from one single party. Control variables are the same as in Tables 2 and 4. Robust errors are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.010.

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. In the end, Republicans filled 200 of these, while Democrats filled 235, equating to a net loss for Republicans of 35 seats. As shown in Section 3, the China tariffs helped Republicans at the midterm. In this section, we quantitatively assess how many of the seats won by Republicans would have been lost without Trump's China tariffs, through artificially removing the pro-Republican effect of Trump's China tariffs. The pro-Republican effect is computed through combining the marginal pro-Republican effect of tariff exposure estimated earlier with observed local tariff exposure. In other words, the counterfactual election outcomes reported in this section are extrapolated by assuming locally invariant pro-Republican effects and inserting locally variant tariff exposure.

The Republican candidate of congressional district (hereafter, district) d won the election if she

Table 12: 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	-0.007	0.001	-0.006
	(0.006)	(0.002)	(0.006)
Control variables	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Observations	3698	1046	724
Adjusted R-squared	0.281	0.423	0.416
Panel B: 2SLS Results			
Second stage:			
Trump tariff exposure	-0.005	0.001	-0.009
	(0.007)	(0.002)	(0.006)
Control variables	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Observations	3698	1046	724
Adjusted R-squared	0.067	0.158	0.213
First stage:			
MIC2025	48.472***	69.277***	45.156***
	(5.083)	(3.435)	(1.529)

Column (1) uses the full sample. Columns (2) and (3) limit the sample to the observations 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). Unlike previous tables, this table does not have columns related to Republican and Democratic incumbents because the incumbents in the year 2018 (elected in the year 2016) were not incumbents in the year 2016 (elected in the year 2014). Control variables are the same as in Tables 2 and 4. Robust errors are clustered at the state level. *** p<0.010.

received a larger share of the district's votes, namely if

$$Repub\_Share_d \equiv \frac{Repub\_Votes_d}{Total\_Votes_d} > Dem\_Share_d \equiv \frac{Dem\_Votes_d}{Total\_Votes_d}. \tag{8}$$

She lost the election if the inequality reverses. We use the 2SLS estimate $\hat{\alpha}_1^{2SLS}$ to construct a counterfactual share of the Republican candidate in each district d. There are two approaches to constructing counterfactual shares, depending on which $\hat{\alpha}_1^{2SLS}$ is used. The two approaches can cross-validate each other. Below, we elaborate on both approaches.

The first approach uses county-level estimated $\hat{\alpha}_1^{2SLS}$, which comes from our primary 2SLS specification (i.e., column (1) in Panel A of Table 4). The counterfactual share of the Republican candidate in county c is

$$\widetilde{R}_{c,2018} = R_{c,2018} - \hat{\alpha}_1^{2SLS} \times TrumpTariffExpo_c. \tag{9}$$

The counterfactual Republican vote share in district d corresponding to county c is:

$$\widetilde{Repub\_Share}_d \equiv \frac{\sum_{c\in d} \widetilde{R}_{c,2018} \times Total\_Votes_c}{Total\_Votes_d}. \quad (10)$$

The subscript $\{c \in d\}$ in equation (10) denotes all counties associated with congressional district d.[28] As counterparts of shares (9) and (10), we have counterfactual Democratic candidate vote shares at the county level:

$$\widetilde{D}_{c,2018} = D_{c,2018} + \hat{\alpha}_1^{2SLS} \times TrumpTariffExpo_c, \quad (11)$$

and at the district level:

$$\widetilde{Dem\_Share}_d \equiv \frac{\sum_{c\in d} \widetilde{D}_{c,2018} \times Total\_Votes_c}{Total\_Votes_d}. \quad (12)$$

The $D_{c,2018}$ in equation (11) is the share of votes received by Democratic house candidates in county c.[29]

The second approach uses the district-level estimated $\hat{\alpha}_1^{2SLS}$, which comes from the robustness check in Section 4.4 (i.e., column (1) in Panel B of Table 10). The counterfactual share of the Republican candidate in district d is

$$\widetilde{Repub\_Share}_d \equiv R_{d,2018} - \hat{\alpha}_1^{2SLS} \times TrumpTariffExpo_d, \quad (13)$$

while the counterfactual Democratic vote share in district d is:

$$\widetilde{Dem\_Share}_d \equiv D_{d,2018} + \hat{\alpha}_1^{2SLS} \times TrumpTariffExpo_d. \quad (14)$$

By taking either approach above, we can 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. The party with a greater district-level counterfactual share would have won district d without Trump's China tariffs.

Since Trump's China tariffs favored the Republican candidates, the counterfactual analysis is relevant only to the 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 either (i) narrowly won or (ii) flipped (i.e., the districts switched from Democratic to Republican control) according to the analysis team of *The New York Times*, and

[28] We define a county as associated with a district as long as part of the county is located in the district. The counterfactual election outcome in a district stems from the application of inequality (8) to all associated counties in the district. Although associated counties might be double-counted across districts, the potential inaccuracy applies to both sides of inequality (8) and therefore they counteract each other to mitigate potential double-counting.

[29] $D_{c,2018}$ 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.

conduct counterfactual analysis on those districts.[30]

For robustness, we use three parameterizations to formulate an interval of $\hat{\alpha}_1^{2SLS}$: $\hat{\alpha}_1^{2SLS}-$ standard error, $\hat{\alpha}_1^{2SLS}$, and $\hat{\alpha}_1^{2SLS}+$ standard error. In theory, the last (first) parameterization tends to overstate (understate) the positive impact of the China tariffs on the Republican winnings. The three parameterizations are denoted by 1 to 3. The two approaches mentioned earlier are both used, labeled as A and B, respectively. The first set of counterfactual election outcomes are reported in Table 13 as six panels (A1 to B3). Out of the 27 districts, two to five would have been lost without Trump's China tariffs. The two robust cases are Georgia District 7 and New York District 27. The second set of counterfactual election outcomes are reported in Table 14. Out of the nine districts flipped by Republicans, one (North Carolina District 9) would not have flipped.[31] In both tables, the results between and within the two approaches are close and stable. Evidently, all else held equal, Republicans would have performed worse without the tariffs.

[30] Details of these districts are provided in Appendix A.1.

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

Table 13: Counterfactual Analysis (Congressional Districts Narrowly Won by Republicans)

	Panel A1			Panel B1			Panel A2			Panel B2			Panel A3			Panel B3		
Dist.	Rep.	Dem.	Out.	Rep.	Dem.	Out.	Rep.	Dem.	Out.	Rep.	Dem.	Out.	Rep.	Dem.	Out.	Rep.	Dem.	Out.
Alaska	0.531	0.465	Win	0.531	0.465	Win	0.530	0.465	Win	0.531	0.465	Win	0.530	0.465	Win	0.531	0.465	Win
Calif. 50	0.507	0.493	Win	0.507	0.493	Win	0.502	0.498	Win	0.494	0.506	Lose	0.496	0.504	Lose	0.481	0.519	Lose
Fla. 6	0.563	0.437	Win	0.563	0.437	Win	0.562	0.438	Win	0.562	0.438	Win	0.562	0.438	Win	0.561	0.439	Win
Fla. 16	0.545	0.455	Win	0.545	0.455	Win	0.544	0.456	Win	0.543	0.457	Win	0.543	0.457	Win	0.542	0.458	Win
Fla. 18	0.542	0.458	Win	0.542	0.458	Win	0.542	0.458	Win	0.542	0.458	Win	0.542	0.458	Win	0.541	0.459	Win
Fla. 25	0.602	0.398	Win	0.602	0.398	Win	0.601	0.399	Win	0.600	0.400	Win	0.600	0.400	Win	0.597	0.403	Win
Ga. 7	0.499	0.501	Lose	0.499	0.501	Lose	0.498	0.502	Lose	0.497	0.503	Lose	0.498	0.502	Lose	0.495	0.505	Lose
Ill. 12	0.515	0.455	Win	0.515	0.455	Win	0.515	0.455	Win	0.514	0.456	Win	0.514	0.456	Win	0.513	0.457	Win
Ill. 13	0.503	0.497	Win	0.503	0.497	Win	0.502	0.498	Win	0.502	0.498	Win	0.502	0.498	Win	0.500	0.500	Win
Iowa 4	0.503	0.470	Win	0.503	0.470	Win	0.503	0.471	Win	0.503	0.471	Win	0.503	0.471	Win	0.502	0.471	Win
Mich. 6	0.502	0.458	Win	0.502	0.458	Win	0.501	0.458	Win	0.500	0.459	Win	0.501	0.459	Win	0.499	0.460	Win
Minn. 8	0.507	0.452	Win	0.507	0.452	Win	0.506	0.452	Win	0.506	0.453	Win	0.506	0.453	Win	0.506	0.453	Win
Mo. 2	0.508	0.476	Win	0.508	0.476	Win	0.506	0.478	Win	0.504	0.480	Win	0.505	0.479	Win	0.499	0.485	Win
Mont.	0.509	0.463	Win	0.509	0.463	Win	0.509	0.463	Win	0.508	0.463	Win	0.508	0.463	Win	0.508	0.463	Win
Neb. 2	0.508	0.492	Win	0.508	0.492	Win	0.508	0.492	Win	0.506	0.494	Win	0.507	0.493	Win	0.504	0.496	Win
N.Y. 24	0.524	0.475	Win	0.524	0.475	Win	0.523	0.475	Win	0.522	0.476	Win	0.523	0.476	Win	0.521	0.478	Win
N.Y. 27	0.487	0.492	Lose	0.487	0.492	Lose	0.484	0.494	Lose	0.481	0.498	Lose	0.482	0.496	Lose	0.475	0.503	Lose
N.C. 2	0.512	0.459	Win	0.512	0.459	Win	0.511	0.460	Win	0.510	0.461	Win	0.510	0.461	Win	0.509	0.462	Win
Ohio 1	0.507	0.475	Win	0.507	0.475	Win	0.504	0.479	Win	0.499	0.484	Win	0.500	0.482	Win	0.491	0.492	Lose
Pa. 16	0.511	0.478	Win	0.513	0.476	Win	0.509	0.480	Win	0.509	0.480	Win	0.506	0.483	Win	0.505	0.484	Win
Tex. 22	0.508	0.470	Win	0.508	0.470	Win	0.505	0.473	Win	0.501	0.478	Win	0.502	0.476	Win	0.493	0.485	Win
Tex. 23	0.491	0.488	Win	0.491	0.488	Win	0.490	0.489	Win	0.489	0.490	Lose	0.489	0.489	Lose	0.488	0.491	Lose
Va. 5	0.531	0.467	Win	0.531	0.467	Win	0.531	0.467	Win	0.531	0.467	Win	0.531	0.467	Win	0.531	0.468	Win
Wash. 3	0.525	0.475	Win	0.525	0.475	Win	0.525	0.475	Win	0.524	0.476	Win	0.524	0.476	Win	0.522	0.478	Win
Wash. 5	0.546	0.454	Win	0.546	0.454	Win	0.546	0.454	Win	0.545	0.455	Win	0.545	0.455	Win	0.543	0.457	Win
W.Va. 3	0.563	0.437	Win	0.563	0.437	Win	0.563	0.437	Win	0.563	0.437	Win	0.563	0.437	Win	0.562	0.438	Win
Wis. 1	0.542	0.426	Win	0.543	0.426	Win	0.541	0.427	Win	0.539	0.430	Win	0.539	0.429	Win	0.535	0.433	Win

This table presents the counterfactual analysis for congressional districts narrowly won by Republicans. Panels A1 and B1 use the original coefficient minus one standard error. Panels A2 and B2 use the original coefficient, Panel A3 and B3 use the original coefficient plus one standard error. Coefficient and standard error in Panels A1, A2, and A3 (respectively, B1, B2 and B3) are county-level 2SLS estimates from column (1) in Panel A of Table 4 (respectively, district-level 2SLS estimates from column (1) in Panel B of Table 10).

Table 14: Counterfactual Analysis (Congressional Districts Flipped by Republicans)

	Panel A1			Panel B1			Panel A2			Panel B2			Panel A3			Panel B3		
Dist.	Rep.	Dem.	Out.	Rep.	Dem.	Out.	Rep.	Dem.	Out.	Rep.	Dem.	Out.	Rep.	Dem.	Out.	Rep.	Dem.	Out.
Fla.15	0.528	0.472	Win	0.528	0.472	Win	0.527	0.473	Win	0.526	0.474	Win	0.526	0.473	Win	0.524	0.476	Win
Kan.2	0.476	0.468	Win	0.476	0.468	Win	0.476	0.468	Win	0.476	0.469	Win	0.476	0.469	Win	0.475	0.469	Win
Ky.6	0.509	0.479	Win	0.509	0.479	Win	0.509	0.479	Win	0.508	0.479	Win	0.509	0.479	Win	0.507	0.480	Win
Minn.1	0.501	0.497	Win	0.501	0.497	Win	0.501	0.497	Win	0.500	0.498	Win	0.500	0.498	Win	0.500	0.498	Win
N.C.9	0.490	0.492	Lose	0.490	0.492	Lose	0.488	0.494	Lose	0.486	0.495	Lose	0.487	0.495	Lose	0.483	0.499	Lose
N.C.13	0.512	0.459	Win	0.512	0.459	Win	0.510	0.461	Win	0.507	0.464	Win	0.508	0.463	Win	0.503	0.468	Win
Ohio 12	0.513	0.474	Win	0.513	0.474	Win	0.512	0.474	Win	0.511	0.476	Win	0.511	0.475	Win	0.509	0.478	Win
Pa.1	0.509	0.491	Win	0.510	0.490	Win	0.507	0.493	Win	0.507	0.493	Win	0.505	0.495	Win	0.504	0.496	Win
Pa.10	0.511	0.489	Win	0.513	0.487	Win	0.510	0.490	Win	0.512	0.488	Win	0.509	0.491	Win	0.511	0.489	Win

This table presents the counterfactual analysis for congressional districts flipped by Republicans. Panels A1 and B1 use the original coefficient minus one standard error. Panels A2 and B2 use the original coefficient, Panel A3 and B3 use the original coefficient plus one standard error. Coefficient and standard error in Panels A1, A2, and A3 (respectively, B1, B2 and B3) are county-level 2SLS estimates from column (1) in Panel A of Table 4 (respectively, district-level 2SLS estimates from column (1) in Panel B of Table 10).

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 political commentators (e.g., Mayeda (2018) and Rappeport (2020)), but we qualitatively confirm them, quantitatively estimate them, and predict counterfactual election outcomes for 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 began entering into US campaign narratives in the early 1980s, which was far earlier than the onset of the China 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 in 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 6 July 2018, Tranche 1 took effect. On 23 August 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 24 September 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 1 January 2019. The actual effective date was later postponed twice, in December 2018 and February 2019. They finally became effective on 10 May 2019. The effective tariffs used in our robustness checks refer to those that had been effective by the time of the midterm elections (6 November 2018), namely the 10 percent additional tariffs, effective since 24 September 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 2010 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. 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).

American Community Survey (ACS). The data were downloaded from 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.

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

Gini coefficient. The Gini coefficient data, as a measure of county-level income inequality, were downloaded from the US Census Bureau website: https://www.census.gov/topics/income-poverty/income-inequality/data/data-tables/acs-data-tables.html (Table B19083, 2013-2017).

China's industrial competition. China's industrial competition is measured with the China-related trade shock constructed by Autor et al. (2013) and provided in their AEA online appendix. Their original data are at the commuting zone (czone) level. David Dorn's website provides the czone-county mapping (see E7 on https://www.ddorn.net/data.htm).

Population density. The population density data were downloaded from the US Census Bureau website: https://covid19.census.gov/datasets/USCensus::average-household-size-and-population-density-county/explore?location=7.318687%2C0.315550%2C2.69&showTable=true.

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 "toss-up seats." We extracted the toss-up 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 Details of the Made in China 2025 Initiative

The Made-in-China 2025 Initiative (hereafter, MIC2025) was released by the Chinese State Council on 19 May 2020. Its full text is publicly available at http://www.gov.cn/zhengce/content/2015-05/19/content_9784.htm, accompanied by a technology roadmap released in October 2015 and downloadable at http://www.cm2025.org/uploadfile/2016/0321/20160321015412313.pdf. The initiative aims to transform China into a global manufacturing leader in the production of high value added products. It encourages the use of private and state funds to conduct research and development (R&D). We manually matched MIC2025-related products with four-digit HS codes through the similarities between product descriptions in MIC2025 and 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 text inference. First, we identify matches based on direct text relevance. For example, MIC2025 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-related product. The second type of matches is through text inference based on MIC2025 descriptions. For example, MIC2025 specifies "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-related 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 matches is through text inference based on HS-code 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 MIC2025.

A.3 Trump's H-1B and Tax Reforms

In this appendix, we examine whether two contemporary reforms carried out by the Trump administration, both of which involve sector heterogeneity, could explain the Republican midterm performance. Trump has been 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 18 April 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."[32] 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

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

2018, up from 7% in Fiscal Year 2017.[33] Meanwhile, Trump, who had advocated for corporate tax cuts during his campaign, signed the Tax Cuts and Jobs Act (TCJA) in December 2017.[34] The TCJA was introduced by Republicans and passed largely along party lines in both chambers of Congress. Effective 1 January 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.[35] 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 1 October through 30 September), the 2018 H-1B approvals had all been completed by the time of the midterm elections. As shown in Figure A1, the number of approvals declined significantly in 2018, affecting Sector 54 ("Professional, Scientific, and Technical Services") the most. The approvals in some traditional 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 A1, the tax savings due to the TCJA are unsurprisingly concentrated in the manufacturing sector and the finance and insurance sector.

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 A5 and A6. The results resemble those we report in the main text.

[33] See Table 7 in USCIS (2018).
[34] See Nunns et al. (2016) for an analysis of Trump's tax proposals during his presidential campaign.
[35] See Appendix A.1 for data details.

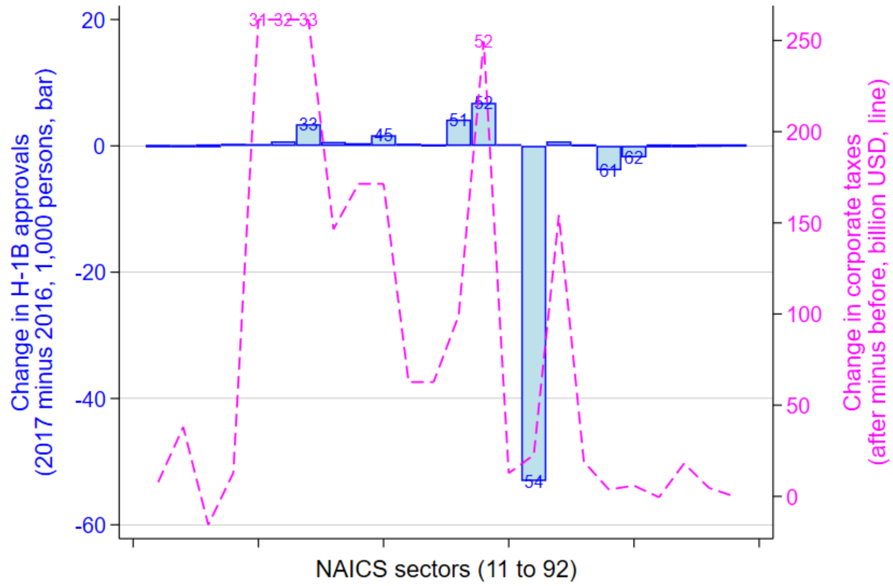

Figure A1:

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

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

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

Equation (1) implies

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

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) .

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: The OLS Results (Full)

	(1)	(2)	(3)	(4)	(5)
Dep. variable:	Difference in the Republican vote share (2018 minus 2016)				
Panel A: Baseline Results					
Sample:	All	Red	Blue	Republican incumbent	Democratic incumbent
Trump tariff exposure	0.007***	0.008***	0.003	0.005***	0.008**
	(0.002)	(0.002)	(0.003)	(0.001)	(0.003)
Manufacturing share	-0.054	-0.102*	-0.090**	-0.024	-0.113**
	(0.032)	(0.056)	(0.039)	(0.045)	(0.050)
Median wage (log)	7.182	-16.401	-10.483	7.351	-3.868
	(7.374)	(9.464)	(13.142)	(7.161)	(12.284)
Labor participation rate	-0.206*	-0.063	-0.099	-0.145	0.032
	(0.119)	(0.212)	(0.390)	(0.154)	(0.271)
Unemployment rate	0.750**	-0.082	-0.699	0.620**	0.691
	(0.345)	(0.336)	(0.923)	(0.295)	(0.672)
Population (log)	-0.848	-0.952	0.931	-1.092	-1.205
	(0.936)	(0.833)	(1.549)	(0.656)	(1.510)
High school	0.706***	0.168	1.539**	0.289*	1.666***
	(0.211)	(0.213)	(0.642)	(0.162)	(0.444)
College degree	0.159	0.541**	0.537**	0.051	0.239
	(0.211)	(0.206)	(0.246)	(0.186)	(0.387)
Bachelor degree or higher	0.454*	0.541**	1.227**	0.101	1.243***
	(0.264)	(0.177)	(0.438)	(0.235)	(0.440)
Black	0.027	-0.170	0.473**	0.055	0.156
	(0.114)	(0.211)	(0.215)	(0.131)	(0.162)
Asian	0.075	0.128	-0.302	0.386**	-0.108
	(0.283)	(0.242)	(0.452)	(0.149)	(0.372)
Hispanic	0.107	0.208	0.197	0.121	0.160
	(0.102)	(0.150)	(0.159)	(0.105)	(0.133)
Male	-0.066	-0.022	1.269	-0.351	1.126
	(0.429)	(0.277)	(1.127)	(0.231)	(1.029)
Evangelical Protestant	-1.058	-1.695	0.659	-10.046	18.918
	(9.357)	(12.519)	(17.443)	(8.342)	(17.701)
Mainline Protestant	-0.788	-3.815	26.398	-13.205	23.982
	(9.667)	(14.647)	(19.152)	(8.469)	(17.374)
Catholic	1.326	0.845	5.818	-9.332	15.401
	(12.069)	(14.573)	(20.579)	(10.586)	(16.887)
Orthodox	59.742	-12.409	368.448	-23.252	272.558
	(79.643)	(12.573)	(308.960)	(25.432)	(210.740)
Black Protestant	2.765	22.295	-4.738	-6.832	16.758
	(22.087)	(33.749)	(38.118)	(24.854)	(26.408)
Female candidate (0 or 1)	0.079	2.322**	-0.158	0.894	-0.234
	(0.374)	(0.895)	(0.328)	(0.824)	(0.471)
Population density	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
Gini	-11.108	-65.850**	-12.532	-34.970**	-16.418
	(22.647)	(29.660)	(35.985)	(15.244)	(35.927)
China-related trade shock	-0.059	0.087	0.714**	-0.034	-0.031
	(0.179)	(0.198)	(0.284)	(0.143)	(0.344)
Age group sharesΔ	Yes	Yes	Yes	Yes	Yes
Observations	3700	1047	724	2888	811
Adjusted R-squared	0.262	0.274	0.412	0.247	0.323

Panel B: Robustness Checks				
Specification:§	Without exempted products	Binary tariffs	Alternative exposure formula	Alternative weights
Trump tariff exposure	0.007***	0.081***	0.007***	0.007***
	(0.002)	(0.022)	(0.002)	(0.002)
Manufacturing share	-0.054	-0.052	-0.054	-0.066*
	(0.032)	(0.033)	(0.032)	(0.034)
Median wage (log)	7.248	7.045	7.185	5.983
	(7.369)	(7.411)	(7.376)	(7.583)
Labor participation rate	-0.206*	-0.205*	-0.206*	-0.268**
	(0.118)	(0.120)	(0.119)	(0.127)
Unemployment rate	0.755**	0.744**	0.749**	0.703**
	(0.345)	(0.349)	(0.345)	(0.337)
Population (log)	-0.861	-0.779	-0.846	-0.957
	(0.934)	(0.961)	(0.936)	(0.855)
High school	0.707***	0.709***	0.706***	0.725***
	(0.210)	(0.209)	(0.211)	(0.217)
College degree	0.161	0.156	0.158	0.229
	(0.211)	(0.206)	(0.210)	(0.216)
Bachelor degree or higher	0.456*	0.458*	0.454*	0.575**
	(0.264)	(0.259)	(0.264)	(0.277)
Black	0.027	0.029	0.027	0.066
	(0.114)	(0.114)	(0.114)	(0.123)
Asian	0.075	0.078	0.075	0.020
	(0.282)	(0.285)	(0.283)	(0.289)
Hispanic	0.107	0.105	0.107	0.111
	(0.102)	(0.101)	(0.102)	(0.102)
Male	-0.065	-0.044	-0.065	-0.117
	(0.428)	(0.434)	(0.429)	(0.402)
Evangelical Protestant	-1.067	-0.982	-1.054	0.791
	(9.352)	(9.442)	(9.360)	(9.193)
Mainline Protestant	-0.811	-0.921	-0.786	2.203
	(9.658)	(9.770)	(9.668)	(9.329)
Catholic	1.288	1.314	1.327	4.791
	(12.061)	(12.093)	(12.070)	(11.764)
Orthodox	59.766	59.622	59.794	54.459
	(79.613)	(79.988)	(79.657)	(94.179)
Black Protestant	2.732	2.151	2.778	-1.886
	(22.047)	(22.123)	(22.089)	(22.696)
Female candidate (0 or 1)	0.079	0.080	0.079	0.094
	(0.373)	(0.374)	(0.374)	(0.404)
Population density	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Gini	-11.135	-11.490	-11.098	-15.091
	(22.666)	(22.447)	(22.662)	(24.306)
China-related trade shock	-0.060	-0.051	-0.058	0.017
	(0.178)	(0.181)	(0.179)	(0.196)
Age group sharesΔ	Yes	Yes	Yes	Yes
Observations	3700	3700	3700	3700
Adjusted R-squared	0.262	0.261	0.261	0.279

This table presents the full OLS results. Panel A: Column (1) uses the full sample, where sample size 3,700 refers to all county-district duplets with nonmissing depndent and explanatory variables. Columns (2) and (3) limit the sample to the observations 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 observations having incumbents from one single party. Panel B: § See Section 3.1 for the details of each check (regression specifications are otherwise the same as in column (1) of Panel A). Both Panels: Δ Age group shares include Age 16-19, Age 20-24, Age 25-29, Age 30-34, Age 35-44, Age 45-54, Age 55-59, Age 60-64, and Age 65-74. Robust errors are clustered at the state level.* p<0.10, ** p<0.05, *** p<0.010.

Table A3: The 2SLS Results (Full)

	(1)	(2)	(3)	(4)	(5)
Dep. variable:	Difference in the Republican vote share (2018 minus 2016)				
Panel A: Baseline Results					
Sample:	All	Red	Blue	Republican incumbent	Democratic incumbent
Trump tariff exposure	0.006***	0.009***	0.007***	0.003	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Manufacturing share	-0.054*	-0.099	-0.100**	-0.041	-0.116**
	(0.032)	(0.056)	(0.044)	(0.038)	(0.052)
Median wage (log)	6.997	-16.539	-7.338	6.601	-3.489
	(7.077)	(9.456)	(11.719)	(6.724)	(12.217)
Labor participation rate	-0.199*	-0.070	-0.132	-0.102	0.019
	(0.112)	(0.212)	(0.370)	(0.161)	(0.263)
Unemployment rate	0.735**	-0.090	-0.430	0.562*	0.717
	(0.328)	(0.339)	(0.742)	(0.280)	(0.669)
Population (log)	-0.725	-0.993	0.053	-0.681	-1.592
	(0.805)	(0.837)	(1.124)	(0.550)	(1.402)
High school	0.697***	0.163	1.531**	0.265	1.693***
	(0.224)	(0.215)	(0.631)	(0.175)	(0.462)
College degree	0.142	0.542**	0.616*	0.008	0.309
	(0.226)	(0.206)	(0.309)	(0.207)	(0.399)
Bachelor degree or higher	0.439	0.543***	1.279**	0.052	1.299***
	(0.284)	(0.177)	(0.464)	(0.255)	(0.470)
Black	0.025	-0.172	0.478**	0.060	0.162
	(0.113)	(0.212)	(0.209)	(0.128)	(0.163)
Asian	0.076	0.119	-0.306	0.467**	-0.111
	(0.286)	(0.243)	(0.433)	(0.177)	(0.364)
Hispanic	0.104	0.205	0.181	0.114	0.173
	(0.103)	(0.148)	(0.152)	(0.110)	(0.139)
Male	-0.054	-0.039	1.228	-0.301	1.102
	(0.407)	(0.276)	(1.105)	(0.225)	(1.004)
Evangelical Protestant	-0.445	-1.811	0.608	-9.085	16.732
	(9.105)	(12.471)	(18.491)	(8.458)	(17.216)
Mainline Protestant	0.054	-3.837	22.706	-11.791	20.922
	(9.263)	(14.612)	(20.110)	(8.332)	(15.873)
Catholic	2.023	1.094	4.341	-8.251	12.987
	(11.932)	(14.504)	(21.629)	(10.247)	(17.392)
Orthodox	59.673	-12.481	386.191	-23.798	276.394
	(79.640)	(12.493)	(320.290)	(25.906)	(213.180)
Black Protestant	3.071	22.755	-2.577	-7.509	16.472
	(21.997)	(33.858)	(37.052)	(24.173)	(25.984)
Female candidate (0 or 1)	0.083	2.323**	-0.190	0.894	-0.245
	(0.373)	(0.898)	(0.335)	(0.824)	(0.467)
Population density	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
Gini	-9.698	-67.609**	-23.658	-28.370*	-20.661
	(22.849)	(29.532)	(37.808)	(15.255)	(36.093)
China-related trade shock	-0.058	0.085	0.691**	-0.037	-0.039
	(0.179)	(0.197)	(0.290)	(0.143)	(0.342)
Age group sharesΔ	Yes	Yes	Yes	Yes	Yes
Observations	3700	1047	724	2888	811
Adjusted R-squared	0.101	0.243	0.288	0.081	0.176
First stage:					
MIC2025	77.206***	67.912***	80.611***	73.680***	74.116***
	(3.561)	(0.334)	(4.221)	(6.099)	(2.601)

Panel B: Robustness Checks				
Specification:§	Without exempted products	Binary tariffs	Alternative exposure formula	Alternative weights
Trump tariff exposure	0.006***	0.076***	0.006***	0.007***
	(0.002)	(0.025)	(0.002)	(0.002)
Manufacturing share	-0.054*	-0.053	-0.054*	-0.067**
	(0.032)	(0.032)	(0.032)	(0.033)
Median wage (log)	7.044	6.945	7.003	5.834
	(7.065)	(7.113)	(7.079)	(7.346)
Labor participation rate	-0.199*	-0.201*	-0.199*	-0.260**
	(0.112)	(0.112)	(0.112)	(0.120)
Unemployment rate	0.739**	0.736**	0.734**	0.690**
	(0.328)	(0.328)	(0.328)	(0.322)
Population (log)	-0.728	-0.710	-0.725	-0.821
	(0.805)	(0.805)	(0.805)	(0.747)
High school	0.697***	0.704***	0.697***	0.718***
	(0.224)	(0.226)	(0.224)	(0.228)
College degree	0.143	0.146	0.142	0.212
	(0.227)	(0.226)	(0.226)	(0.229)
Bachelor degree or higher	0.439	0.449	0.439	0.559*
	(0.284)	(0.284)	(0.284)	(0.294)
Black	0.025	0.028	0.025	0.065
	(0.113)	(0.114)	(0.113)	(0.122)
Asian	0.076	0.079	0.076	0.022
	(0.286)	(0.287)	(0.286)	(0.292)
Hispanic	0.104	0.103	0.104	0.107
	(0.103)	(0.102)	(0.103)	(0.103)
Male	-0.053	-0.038	-0.054	-0.102
	(0.407)	(0.410)	(0.407)	(0.378)
Evangelical Protestant	-0.410	-0.627	-0.452	1.479
	(9.106)	(9.048)	(9.105)	(9.016)
Mainline Protestant	0.094	-0.421	0.041	3.152
	(9.263)	(9.148)	(9.263)	(9.031)
Catholic	2.039	1.723	2.013	5.574
	(11.922)	(11.901)	(11.932)	(11.646)
Orthodox	59.690	59.588	59.722	54.239
	(79.607)	(80.005)	(79.658)	(94.346)
Black Protestant	3.063	2.363	3.077	-1.615
	(21.966)	(21.951)	(22.001)	(22.645)
Female candidate (0 or 1)	0.083	0.083	0.083	0.099
	(0.372)	(0.373)	(0.373)	(0.404)
Population density	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Gini	-9.621	-10.645	-9.714	-13.250
	(22.849)	(22.581)	(22.853)	(24.193)
China-related trade shock	-0.059	-0.051	-0.058	0.018
	(0.179)	(0.181)	(0.179)	(0.196)
Age group shares∆	Yes	Yes	Yes	Yes
Observations	3700	3700	3700	3700
Adjusted R-squared	0.102	0.101	0.101	0.106
First stage :				
MIC2025	74.661***	6.155***	76.931***	77.442***
	(3.820)	(0.269)	(3.573)	(3.510)

This table presents the full 2SLS results. Panel A: Column (1) uses the full sample, where sample size 3,700 refers to all county-district duplets with nonmissing depndent and explanatory variables. Columns (2) and (3) limit the sample to the observations 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 observations having incumbents from one single party. Panel B: § See Section 3.2 for the details of each check (regression specifications are otherwise the same as in column (1) of Panel A). Both Panels: ∆ Age group shares include Age 16-19, Age 20-24, Age 25-29, Age 30-34, Age 35-44, Age 45-54, Age 55-59, Age 60-64, and Age 65-74. Robust errors are clustered at the state level.* p<0.10, ** p<0.05, *** p<0.010.

Table A4: Voter Turnout

	(1)	(2)	(3)	(4)	(5)
Dep. variable:	Difference in Voter Turnout (2018 minus 2016)				
Sample:	All	Red	Blue	Republican incumbent	Democratic incumbent
Panel A: OLS Results					
Trump tariff exposure	0.001	0.001	-0.000	0.002	0.001
	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
Control variables†	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	3700	1047	724	2888	811
Adjusted R-squared	0.795	0.590	0.963	0.729	0.883
Panel B: 2SLS Results					
Second stage:					
Trump tariff exposure	0.002	0.001	0.001	0.002	0.002
	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)
Control variables†	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	3700	1047	724	2888	811
Adjusted R-squared	0.639	0.478	0.919	0.582	0.741
First stage:					
MIC2025	77.206***	67.912***	80.611***	73.680***	74.116***
	(3.561)	(0.334)	(4.221)	(6.099)	(2.601)

Column (1) uses the full sample. Columns (2) and (3) limit the sample to the observations 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 observations having incumbents from one single party. Control variables are the same as in Tables 2 and 4. Robust errors are clustered at the state level. *** p<0.010.

Table A5: Sector Heterogeneity Check I (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	0.017***	0.021***	0.016***	0.011***	0.021***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.007)
Observations	3700	1047	724	2888	811
Adjusted R-squared	0.264	0.278	0.422	0.244	0.331
OLS Results — H-1B low group					
Trump tariff exposure	0.010***	0.013***	0.000	0.010***	0.010
	(0.003)	(0.004)	(0.007)	(0.003)	(0.006)
Observations	3700	1047	724	2888	811
Adjusted R-squared	0.258	0.270	0.410	0.248	0.316
2SLS Results — H-1B high group					
Trump tariff exposure	0.019***	0.016*	0.024***	0.012***	0.026***
	(0.005)	(0.008)	(0.008)	(0.004)	(0.009)
Observations	3700	1047	724	2888	811
Adjusted R-squared	0.104	0.246	0.301	0.081	0.186
2SLS Results — H-1B low group					
Trump tariff exposure	0.009**	0.014***	0.016**	0.004	0.015**
	(0.004)	(0.004)	(0.005)	(0.003)	(0.006)
Observations	3700	1047	724	2888	811
Adjusted R-squared	0.097	0.239	0.258	0.080	0.166

Column (1) uses the full sample. Columns (2) and (3) limit the sample to the observations 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 observations having incumbents from one single party. Control variables (the same as in Tables 2 and 4) and state fixed effects are included. Robust errors are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.010.

Table A6: Sector Heterogeneity Check II (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	0.011	0.014***	0.040**	0.006*	0.016
	(0.008)	(0.004)	(0.017)	(0.003)	(0.011)
Observations	3700	1047	724	2888	811
Adjusted R-squared	0.248	0.273	0.423	0.237	0.312
OLS Results — Tax saving low group					
Trump tariff exposure	0.009***	0.020**	0.002	0.008***	0.009**
	(0.002)	(0.007)	(0.004)	(0.002)	(0.004)
Observations	3700	1047	724	2888	811
Adjusted R-squared	0.263	0.273	0.411	0.249	0.323
2SLS Results — Tax saving high group					
Trump tariff exposure	0.031*	0.011**	0.070***	0.016*	0.044*
	(0.016)	(0.005)	(0.021)	(0.010)	(0.023)
Observations	3700	1047	724	2888	811
Adjusted R-squared	0.063	0.241	0.297	0.065	0.140
2SLS Results — Tax saving low group					
Trump tariff exposure	0.011***	0.019**	0.013**	0.006***	0.015***
	(0.003)	(0.007)	(0.005)	(0.002)	(0.005)
Observations	3700	1047	724	2888	811
Adjusted R-squared	0.102	0.243	0.261	0.087	0.168

Column (1) uses the full sample. Columns (2) and (3) limit the sample to the observations 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 observations having incumbents from one single party. Control variables (the same as in Tables 2 and 4) and state fixed effects are included. Robust errors are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.010.