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.

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 happened in the last century, when the Republicans, who proposed the Smoot-Hawley Tariff Act and sparked a trade war among industrialized economies in the 1930s, became the party more supportive of free trade in the second half of the century. The Republican-trade relationship is now reaching another critical moment. Donald Trump, who is affiliated with the Republican Party and was elected as the 45th US president, used his executive power to raise tariffs on US imports from China in mid-2018. The congressional elections in November 2018, known as midterm elections since they occurred halfway through a president's four-year term, were 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 Republican house candidates in the

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2018 midterm elections. We construct a measure of each US county's exposure to Trump's China tariffs using the county's employment composition. We find that the Republican Party received more support in 2018 relative to 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 crucial motivation for Trump's China tariffs, as made clear by the Trump administration when it announced the tariffs. As an ambition not yet developed into industrial or trade policies, the MIC2025 influenced the target product list of Trump's China tariffs, but had little reason to affect county-level ballots through other channels on the US side.

By instrumenting county-level China tariff exposure with county-level MIC2025 exposure, we find that 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.

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; Grossman and Helpman, 1994, 1995; 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, 2020; 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 a peaceful world. In a trade war, not only do nations attack one another, but so too do interest groups within each nation fight against each other to influence their nation's response. The trade war initiated by the Trump administration is unique in its political significance. It was launched by a Republican president after the Republican Party's half-century long friendliness towards free trade. His trade war, which set not only China but also multiple industrialized economies as targets, is reminiscent of the last global trade war set in motion by the Republican-sponsored Smoot-Hawley Tariff Act in the 1930s.

The literature on the political consequences of Trump's trade war can be divided into two strands. The first strand examines the interaction between the US and multiple countries during the trade war. This strand gives a comprehensive account of Trump's trade war, which was a multiple-country, back-and-forth process. Fetzer and Schwarz (2021) find that Trump's trade-war targets, including Canada, China, the European Union and Mexico retaliated against the US by targeting US counties that swung from supporting Barack Obama in 2012 to supporting Donald Trump in 2016. Blanchard, Bown, and Chor (2024) find that Trump's tariffs against those countries brought net political losses to the Republicans in 2018. Lake and Nie (2023) find that Trump's tariffs and foreign retaliatory tariffs had opposing effects on the 2020 presidential election. When the trade war is narrowed down to the frontline between the US and China, the political consequence becomes straightforward, as explicated by the second strand of the literature. The studies in this strand have so far focused on the agricultural products spotlighted at the US-China frontline. Chyzh and Urbatsch (2020) find that soybean producers in the US showed less support for the Republicans, and Choi and Lim (2023) find that agricultural subsidies made by the Trump administration to compensate farmers generated support for Trump in the 2020 presidential election.

Our paper, belonging to the second strand of the literature, focuses on the US-China trade confrontation, covers the full product scope, and aims to identify causality with the aforementioned instrumental strategy. The China topic became a point of contention in the US political arena long before China became the second largest economy. It has resurfaced in every election year, as 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.*

Beyond these documented finger-pointing episodes, to our knowledge, there has not been formal empirical evidence confirming that a hawkish stance on China does produce electoral advantages. Our work helps understand the economic role China plays in the US political narrative. The economic literature on the China Syndrome (e.g., Autor et al., 2013; Acemoglu et al., 2016; Pierce and Schott, 2016, 2020) has established that imports of Chinese products have a negative causal impact on US employment rates. Therefore, politicians are expected to gain politically, rather than suffer losses, when they enact economic policies against China before a major election. The potential for these political gains is a crucial logical link in rationalizing the relevance of the China issue to every election. With this missing piece of evidence in place, economists and non-economist academics can formulate a more informed, realistic view when taking on economic and political analyses related to US-China relations.

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 identification and robustness checks. In Section 5, we conclude.

2 Data

2.1 Trump's China Tariffs

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

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

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

[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).

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 distribution 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., 2024; 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 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 Section 4.4 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

[2] County is also chosen as the unit of observation in studies on other aspects of US politics and policies. See, for example, Blanchard et al. (2024), Che et al. (2016), Freund and Sidhu (2017), Jensen et al. (2017), Kriner and Reeves (2012), Lake and Nie (2023), Lu et al. (2018), Pierce and Schott (2020), and Wright (2012).

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 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)). Tailoring their formula to our context, we define county c's exposure to Trump's China tariffs as

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

Here $L_{c,p}/L_p$ is the employment share of county c related to product p within the US, and Δt_p^{Trump} is the additional tariff levied on Chinese product p. If a product p has $\Delta t_p^{Trump} = 0$, it is not counted into the exposure. $TrumpTariffExpo_c$ is essentially a weighted count of local product lines protected by Trump's tariffs: $L_{c,p}/L_p$ adjusts for the geographic concentration of product p's production while Δt_p^{Trump} adjusts for the strength of tariff protection. Consider product p and product p' that are both produced in county c and protected by Trump's tariffs. Product p is produced only in county c (full concentration) while product p' is produced everywhere in the US (full unconcentration). Then the two products should not be equally weighted when aggregated into $TrumpTariffExpo_c$. The same reasoning applies to the scenario where the two tariff rates differ. The two adjustments ensure that the measured influence on county c's economy reflects industrial clusters (industries focally located) and industrial policies (industries focally protected).

Because county-product level employment data are nonexistent, we follow the literature to approximate county-product level employment shares with 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 (see Autor et al. (2013), Acemoglu et al. (2016) and Pierce and Schott (2020) among others; see Autor, Dorn, and Hanson (2016) for a review). Thus, in effect, the exposure measure is

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

where $j(p)$ represents the industry to which product p belongs. 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. In addition to $TrumpTariffExpo_c$ itself, its variants are also used to measure the exposure to Trump's tariffs, as we discuss in later robustness checks.

The geographical distribution of $TrumpTariffExpo_c$ is shown in the upper panel of Figure 1. The geographical distribution of our instrumental variable, displayed in the lower panel thereof, will be discussed later. Table 1 reports the summary statistics of our working sample. We now move on to our empirical specification and findings.

3 Main Findings

3.1 OLS Results

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

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

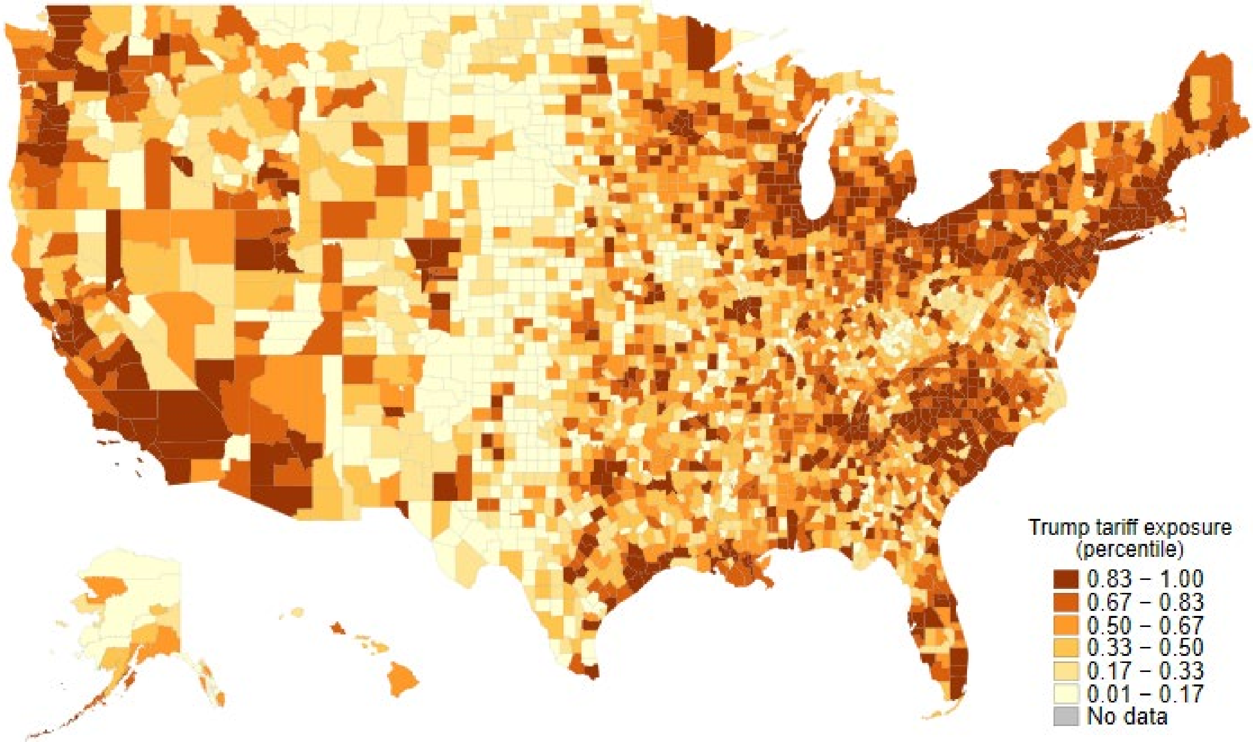
where the dependent variable is the change in the Republican vote share R_c of county c between the house elections of 2018 and the house elections of 2016, measured in percentage points. $TrumpTariffExpo_c$ is the aforementioned tariff exposure measure and $\mathbf{X}_c$ is a vector of control variables. $\gamma_{s(c)}$ 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 house elections of 2018, in order to adjust for the relative importance of counties in determining the election outcome.[3]

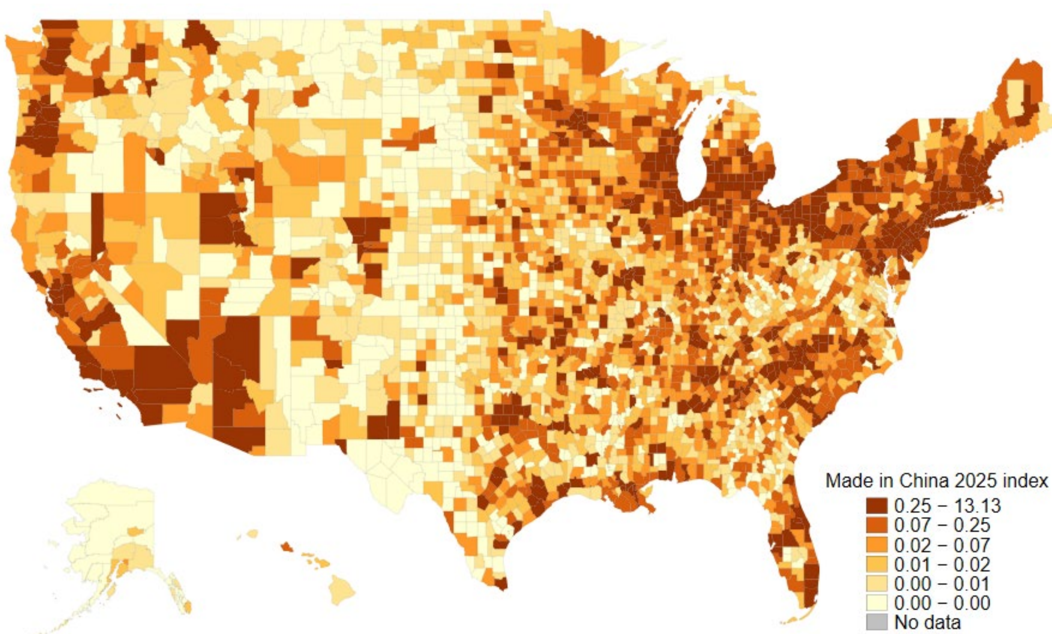
It should be noted that the mean of the dependent variable is -4.15 percentage points, the median -3.26, and the 75th percentile -0.30.[4] The Republican Party had vote-share losses in three quarters of the counties in 2018 relative to 2016. What the coefficient α_1 captures is the *relative* gain or loss of the Republicans. In other words, a positive α_1 does not necessarily mean a larger increase

[3]We use local population as alternative weights to rerun all our results and reach the same findings (available upon request).

[4]Figure A1 is a histogram of the dependent variable.

Figure 1: Exposure to Trump's China Tariffs and China's Made-in-China 2025 Initiative





The upper map displays the percentiles of our main explanatory variable (exposure to Trump's China tariffs; see Section 2.3 for details). The lower map displays the values of our instrumental variable used in 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.
Panel A: Election-related variables†			
Republican vote share 2018	3758	0.59	0.20
Republican vote share 2016	3755	0.63	0.22
Panel B: Main regressor and instrumental variable			
Trump tariff exposure§	3758	28.56	97.91
MIC2025¥	3758	0.43	1.41
Panel C: County characteristics£			
Manufacturing share (%)	3758	30.62	13.14
Median wage (log)	3758	10.82	0.26
Labor participation rate (%)	3758	59.45	7.91
Unemployment rate (%)	3758	6.41	2.90
Population (log)	3758	10.69	1.78
High school (%)	3758	32.32	8.01
College degree (%)	3758	32.28	5.69
Bachelor degree or higher (%)	3758	23.55	10.79
Black (%)	3758	7.59	11.25
Asian (%)	3758	1.61	3.15
Hispanic (%)	3758	7.30	10.58
Male (%)	3758	50.65	3.25
Age 16-29 (%)	3758	17.66	4.11
Age 30-54 (%)	3758	31.08	3.00
Age 55-74 (%)	3758	23.86	4.44
Evangelical protestant adherents (%)	3703	38.18	22.68
Mainline protestant adherents (%)	3703	30.14	17.88
Black protestant adherents (%)	3703	2.55	5.25
Catholic adherents (%)	3703	23.36	21.41
Orthodox adherents (%)	3703	0.34	2.54
Female candidate (0 or 1)	3758	0.41	0.49
Population density (people per square kilometer)	3758	229.05	1279.34
Gini coefficient	3758	0.45	0.04
China-related trade shock	3758	2.76	2.68

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.

in the Republican vote share from 2016 to 2018, but could alternatively imply a smaller decrease from 2016 to 2018. Like the former case, the latter case is also a relative political gain for the Republican candidate in a given county. The gain and loss in this study are all in relative terms, not distinguishing smaller negative changes from larger positive changes.

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 candidates. 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 Democratic presidential candidates (i.e., "blue states" in column (3)) between 1992 and 2012.[5] The results 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 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 the rest of Panel B, we experiment with three variants of exposure measure (1). Recall that exposure measure (1) is essentially a count of affected local industries weighted by geographic concentration and tariff rates. The first variant mutes the tariff-rate weighting by replacing the Trump tariffs with their binary version:

$$TrumpTariffExpo_c^1 = \sum_{p \in c} \frac{L_{c,j(p)}}{L_{j(p)}} \mathbb{1}[\Delta t_p^{Trump} > 0]. \tag{3}$$

The second variant replaces the geographic concentration adjustment $L_{c,j(p)}/L_{j(p)}$ with local in-

[5] Since Trump won several previously blue states in 2016, we do not use the 2016 presidential election results to designate blue states. Nonetheless, with those blue states included in the group of blue states, 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 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 HTSUS product codes.

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	Exposure Variant 1	Exposure Variant 2	Exposure Variant 3	
Trump tariff exposure	0.007***	0.081***	0.007***	0.301**	
	(0.002)	(0.022)	(0.002)	(0.126)	
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	0.258	

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 dependent 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<0.01.

dustrial composition adjustment $L_{c,j(p)}/L_c$:

$$TrumpTariffExpo_c^2 = \sum_{p \in c} \frac{L_{c,j(p)}}{L_c} \Delta t_p^{Trump}. \tag{4}$$

Note that the main variation of $TrumpTariffExpo_c^2$ remains in the tariff-weighted count of affected local products, namely the set $\{p \in c : \Delta t_p^{Trump} > 0\}$. The industrial composition adjustment is simply an alternative way to adjust the count. The third variant is similar to the second but uses industry as the unit of aggregation:

$$TrumpTariffExpo_c^3 = \sum_{j(p) \in c} \frac{L_{c,j(p)}}{L_c} \Delta t_p^{Trump}. \tag{5}$$

The results from the three variants are reported in columns (2) to (4) in Panel B, all delivering findings that resemble the baseline finding from column (1) in Panel A.[10]

3.2 2SLS Results

3.2.1 Instrumental Strategy

The positive association between county-level tariff exposure and support for the 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 HS product 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 admin-

[10] A simple example can illustrate the differences among the three variants. Consider a county with two local industries 1 and 2 equally sized in employment. Industry 1 makes two products, both receiving a tariff shock of a percentage points. Industry 2 makes one product, receiving a tariff shock of b percentage points. Our baseline exposure measure considers the county to be one receiving three separate shocks of magnitudes a, a, and b and will weight and then aggregate them according to the shares of the two industries in their corresponding nationwide employments (i.e., geographic concentration). Variant 1 is the same as the baseline exposure measure in capturing three separate shocks, ignoring rates a, a, and b but still adjusting for geographic concentration. Variant 2 captures three separate shocks, ignoring geographic concentration but weighting the three shocks by industrial composition and rates a, a, and b. Since Variant 2 ignores the rest of the country, we can pinpoint its total magnitude: $0.5a + 0.5a + 0.5b$. Variant 3 captures one shock with a magnitude of $0.5a + 0.5b$. The three variants have different variance and thus the coefficients from the respective regressions are not directly comparable with each other or with the baseline exposure measure.

istration 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, as the foundation of our instrumental strategy, is confirmed by our later statistical analysis.

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 high-tech. Likewise, glass substrate used in making LED glass 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 Chinese 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 poli-

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

[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)).

tics. 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 on the Chinese 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 decoupling policies aiming to turn off the business 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 valid instrumentation. 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 valid instrumentation. The relevance condition is directly testable. In Table 3, Trump's China tariff lists and rates are regressed on whether an import product relates to MIC2025. In Panel A, each observation relates to one four-digit HS product. The independent variable $MIC2025_p$ is an

[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 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.

indicator constructed for each four-digit HS product. The dependent variable is either a China-tariff 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 and $MIC2025_p$ remains at the four-digit level. The dependent variable is either a China-tariff 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 product. 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, 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:

$$MIC2025_c = \sum_{p \in c} \frac{L_{c,j(p)}}{L_{j(p)}} MIC2025_p, \tag{6}$$

where $MIC2025_p$ is the four-digit MIC2025 indicator mentioned above. As before, $j(p)$ represents the industry to which product p belongs. The geographical distribution of $MIC2025_c$ is demonstrated in the lower panel of Figure 1.

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 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] In addition, column (5) in Panel B of Table 4 reports the 2SLS results from the instrument without the weight term $L_{c,j(p)}/L_{j(p)}$. The result is

[16]We also examined, using both OLS and 2SLS, whether the same regression specifications can explain voter turnout. The results are reported in Table A6. Tariff exposure has little explanatory power for voter turnout.

Table 3: Correlation between MIC2025 and Trump's China Tariffs at the Product Level

	(1)	(2)	(3)	(4)	(5)	(6)
	Applied Trump's China tariffs			Applied Trump's China tariffs (without exemptions)		
Dep. Variable:	Indicator **1** (=1 if applied)		New tariff rate (percentage points)	Indicator **1** (=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 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 errors in parentheses, clustered at the two-digit HS product code level. *** p<0.01, ** p<0.05.

similar to the baseline one, indicating that the relevance of the instrument variable comes from the count of MIC2025-related products rather than from the weight term.

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 his party mitigate its losses in the 2018 house elections. 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 (see Che et al. (2016) and Conconi et al. (2020) among others). With the 2SLS estimates, we conduct a counterfactual analysis in Appendix A.3 by subtracting the

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: Difference in the Republican vote share (2018 minus 2016)					
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: 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	Exposure Variant 1	Exposure Variant 2	Exposure Variant 3	MIC2025 as counts
The second stage					
Dep. Variable: Difference in the Republican vote share (2018 minus 2016)					
Trump tariff exposure	0.006***	0.076***	0.006***	0.405***	0.007*
	(0.002)	(0.025)	(0.002)	(0.143)	(0.004)
Control variables	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	3700	3700	3700	3700	3700
Adjusted R-squared	0.102	0.101	0.101	0.106	0.101
The first stage					
Dep. Variable: Trump tariff exposure					
MIC2025	74.661***	6.155***	76.931***	77.206***	10.125***
	(3.820)	(0.269)	(3.573)	(3.561)	(0.833)

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 dependent 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<0.01, * p<0.10.

estimated political gains for Republican house candidates from the votes they received to examine how the midterm election outcome would have changed without Trump's China tariffs.

$MIC2025_c$ is a shift-share instrumental variable (SSIV). An SSIV takes the form of $z_c = \sum_m s_{c,m} g_m$, where c indexes locations, m indexes sectors (e.g., products or industries), g_m represents sector-specific changes, and $s_{c,m}$ is a weight that assigns sector-specific changes to locations.[17] There are two schools in the literature, viewing different elements of SSIVs as exogenous. The first school, represented by Goldsmith-Pinkham, Sorkin, and Swift (2020) (hereafter, GSS), views the shares as exogenous and proposes a Rotemberg decomposition for 2SLS estimation. Their method decomposes a 2SLS estimator into a sum of sector-specific parameters: $\hat{\alpha} = \sum_m \hat{\alpha}_m \hat{\beta}_m$, where $\hat{\alpha}_m$ (known as Rotemberg weight) represents the relative importance of sector m in estimation. GSS recommend checking if there are influential sectors that drive the 2SLS estimation such that the shares are not exogenous enough. The second school, represented by Borusyak, Hull, and Jaravel (2022) (hereafter, BHJ), views g_m as exogenous and recommends converting the location-level regression to a sector-level regression.[18]

Although our setting is relatively closer to the BHJ setting than to the GSS setting, we consider the checks recommended by both schools useful and implement both of them.[19] We define sectors as two-digit HS products. Panel A of Table 5 follows the format used by GSS to implement their check on Autor et al. (2013). The first part demonstrates that the Rotemberg weights in our setting correlate with both sector-specific changes g_m and county-sector employment weights $s_{c,m}$. The second part presents the five sectors with the largest Rotemberg weights. As noted by GSS, examining such top sectors helps expose influential sectors. In our setting, the top sectors have similar weights and none of them display considerable influences. In fact, some of those sectors are not in the spotlight of the trade war. Panel B of Table 5 reports the sector-level 2SLS regression which is equivalent, à la BHJ, to our previous 2SLS regression. The finding turns out to be similar. Specifically, the coefficient of the Trump tariff measure is close to the one in column (1) of Panel A, Table 4.

The results in Table 5 serve as a technical check of our instrumental strategy. The OLS and 2SLS results presented in this section survive a long list of other identification and robustness checks, as we discuss in the next section.

[17] For both methods, the sum of shares $\sum_m s_{c,m}$ need not add up to unity.

[18] Computer programs for the GSS and BHJ routines are available at https://github.com/paulgp/bartik-weight and https://github.com/kylebutts/ssaggregate, respectively.

[19] The employment data we used to construct the weights are from the year 2010, so that it is reasonable to assume them to be exogenous, at least predetermined for the 2018 midterm elections.

Table 5: GSS and BHJ Checks

Panel A: The GSS check (Rotemberg decomposition)

Correlations

	α	g	$var(s)$
α	1		
g	-0.439	1	
$var(s)$	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
Fertilizers	0.046
Vegetable plaiting materials; vegetable products n.e.s.	0.043
Iron and steel	0.042

Panel B: The BHJ check

Dep. variable:	Difference in the Republican vote share (2018 minus 2016)	
Trump tariff exposure	0.004***	0.009**
	(0.000)	(0.005)
Education-related controls	No	Yes
Ethnicity-related controls	No	Yes
Age-related controls	No	Yes
Religion-related controls	No	Yes
Observations	95	95
Adjusted R-squared	0.615	0.731

GSS stands for Goldsmith-Pinkham, Sorkin, and Swift (2020), and BHJ stands for Borusyak, Hull, and Jaravel (2022). See the text for details. ** p<0.05, *** p<0.01.

4 Additional Identification and Robustness Checks

4.1 Sector Heterogeneity

A potential concern over our instrumental variable $MIC2025_p$ is sector heterogeneity. We regress $MIC2025_p$, namely whether product p relates to MIC2025, on sector dummies and use the residuals to construct an instrumental variable $MIC2025^e_c$ with the previous equation (6). This auxiliary regression is 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, this auxiliary instrumental variable $MIC2025_c^e$ 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 6. They resemble those in Table 4, except that the first-stage coefficients become smaller in magnitude (remaining statistically significant). Given the high similarity between Table 4 and Table 6, 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. Thus, we prefer the original $MIC2025_c$ to $MIC2025_c^e$.

Table 6: 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 reg. 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 the 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<0.01.

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 rigorous 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. In Appendix A.4, 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 MIC2025 and the US Economy

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 upper-left graph) and US exports to the rest of the world (the lower-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 upper-right and lower-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 Chinese side show no change in the MIC2025-related trade of China. Panel B of Figure 2 follows the structure of 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.

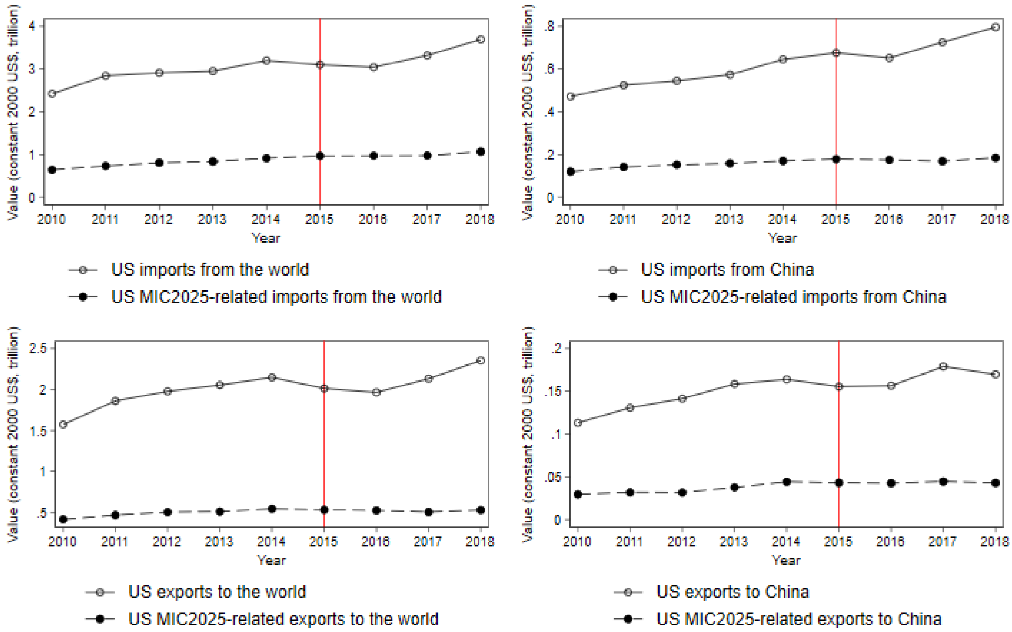
In addition to graphical analysis, we specify the following regression to examine the two countries' imports and exports of MIC2025-related products:

$$\ln T_{pt} = \omega MIC2025_p \times \mathbb{1}[t \geq 2015] + \lambda_{p4} + \lambda_t + \epsilon_{pt}, \tag{7}$$

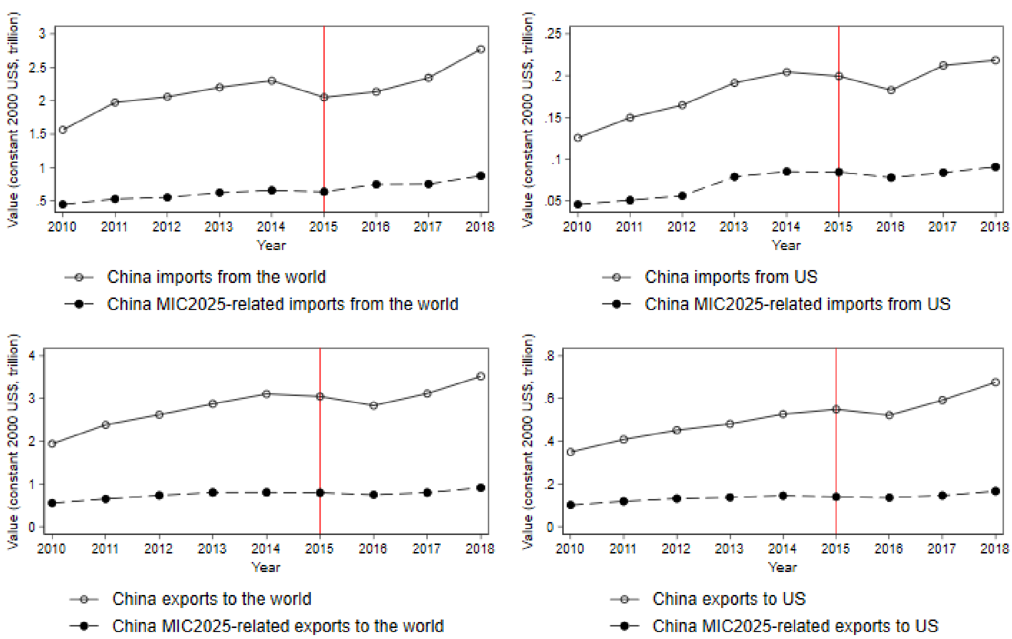
where T_{pt} is trade volume (either imports or exports) of product p of either country in year t. The indicator variable $\mathbb{1}[t \geq 2015]$ captures the presence of MIC2025, and our parameter of interest is ω. Each observation is associated with a six-digit product p in year t, while $MIC2025_p$ remains at the four-digit product level as before. Four-digit product fixed effect λ_{p4} and year fixed effect λ_t are included in the regression. The results are reported in Panel A of Table 7, for the US trade

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

Panel A: The US side



Panel B: The Chinese side



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.

Table 7: 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
Four-digit HS product FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Panel B: The Chinese side				
	From/to the world		From/to the US	
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
Four-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 is statistically significant at the 10 percent (or lower) level.

with the rest of the world (columns (1)-(2)) and the US trade with China (columns (3)-(4)).[20] 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 material trade changes generated by MIC2025 by the time of the midterm elections.

We also use the previously constructed county-level exposure to MIC2025 to explain county-level economic indicators, including median household income, median family income, income

[20]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.

per capita and unemployment rate.[21] As shown in Table 8, $MIC2025_c$ has no association with those five-year averages preceding 2018 or their changes relative to five years ago, except one positive correlation (2018 income per capita). The regressions in Table 8 serve as a placebo check, through which material impact of MIC2025-related products on the local economies can be detected. They support the role of MIC2025 initiative as a forward-looking intention rather than an industrial policy in motion.

Table 8: Economic Indicators and MIC2025-related Products

	(1)	(2)	(3)	(4)
Panel A: Five preceding year average 2018				
Dep. Variable:	ln(Median household income)	ln(Median family income)	ln(Income per capita)	Unemployment rate
MIC2025	0.006	0.005	0.014**	-0.008
	(0.005)	(0.006)	(0.007)	(0.042)
State FE	Yes	Yes	Yes	Yes
Observations	3134	3134	3134	3134
Adjusted R-squared	0.323	0.295	0.266	0.232
Panel B: Five preceding year average 2018 – Five preceding year average 2016				
Dep. Variable:	Diff. in ln(Median household income)	Diff. in ln(Median family income)	Diff. in ln(Income per capita)	Diff. in Unemployment rate
MIC2025	0.000	0.001	0.000	0.007
	(0.001)	(0.001)	(0.000)	(0.015)
State FE	Yes	Yes	Yes	Yes
Observations	3133	3134	3134	3134
Adjusted R-squared	0.217	0.178	0.182	0.327

Various economic indicators are regressed (OLS) on MIC2025. Dependent variables are noted in the table. Robust errors are clustered at the state level. ** p<0.05.

4.3 China's Retaliatory Tariffs

In response to Trump's China tariffs, the Ministry of Commerce of China announced retaliatory tariffs. Such retaliatory tariffs, unfavorable to Trump, are unlikely to yield political gains for the Republicans. The extant studies have found that Trump's tariffs against multiple trade partners

[21] The data source is the American Community Survey (ACS). The ACS uses the US Census definitions: a family consists of two or more people related by birth, marriage, or adoption residing in the same housing unit, while a household consists of all people who occupy a housing unit regardless of relationship. A household may consist of a person living alone or multiple unrelated individuals or families living together.

(not limited to China) actually harmed his party (Blanchard et al., 2024). Specific to China, we construct county-level exposure to China's retaliation, or

$$RetTariffExpo_c = \sum_p \frac{L_{c,j(p)}}{L_{j(p)}} \Delta t_p^{Retaliation}, \tag{8}$$

and include it in the previous OLS and 2SLS regressions. The results are reported in Panel A of Table 9, where column (1) reproduces column (1) in Panel A of Table 4 for the purpose of comparison. In column (2), namely the OLS result, the two exposures have positive and negative coefficients, respectively, though neither of the two exposure measures is statistically significant. We continue to instrument the Trump tariff exposure as before, which does not improve the statistical significance of either coefficient. In column (4), we instrument the retaliatory tariff exposure with the same instrument, and the statistical insignificance remains.[22]

We speculate that the statistical insignificance of both exposure measures is driven by the large overlap between the product lines—and thus tariff lines—of the US-China bilateral trade.[23] Our speculation is supported by a further examination of the two exposure measures. Panel B of Table 9 shows that the retaliatory tariffs are significantly correlated with Trump's China tariffs at both county- and industry-levels. Figure 3 demonstrates the high correlation when different weights, products, and levels of aggregation are used. In particular, high correlation is not solely driven by the weight term $L_{c,j(p)}/L_{j(p)}$ shared by the two county-level exposure measures, since columns (2)–(4) in Panel B of Table 9 and two SIC panels in Figure 3 use industry-level data and thus do not involve weights. As shown, the high correlation exists at the industry level as well. We further delve into the product (HS) level. Figure 4 demonstrates the overlap between Trump's China tariff lines and China's retaliatory tariff lines. Each cell in the heatmaps represents a four-digit HS product line (the first two digits represented by the horizontal axis, and the last two digits by the vertical axis). Pertaining to each four-digit HS product line, the six-digit product lines 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-left panel. We subtract retaliatory tariffs from the heatmap and display the net counts in the lower-left panel. As shown by these two left-side panels, the removal of China's retaliatory tariffs generates a widespread reduction in heat levels but keeps heat distribution largely intact. We conduct the same heat comparison for the Chinese side—that is, netting Trump's tariffs out of China's retaliatory tariffs in count for each cell—and

[22]Instrumenting the retaliatory tariff exposure with MIC2025 is a placebo check. The purpose of this placebo check is not to identify a causal effect but to examine if the statistical significance of the two coefficients improves. In theory, China might protect those products/industries with retaliatory tariffs (the relevance condition of valid instrumentation is satisfied) but then such tariffs arguably influence the support for the Republicans (the exclusion condition of valid instrumentation is questionable here).

[23]The bilateral trade between the US and China has long been characterized by a significant amount of manufacturing outsourcing, see Johnson and Noguera (2012), Kee and Tang (2016), and Los and Timmer (2020) among others for evidence and discussion.

Table 9: Regressions with Both Exposure Measures

	(1)	(2)	(3)	(4)
Panel A: Both exposure measures included				
Dep. variable:	Difference in the Republican vote share (2018 minus 2016)			
Specification	2SLS (reproduced)	OLS	2SLS	2SLS
Instrumented	Trump	n/a	Trump	Chinese
Trump tariff exposure	0.006***	0.007	0.004	0.002
	(0.002)	(0.007)	(0.008)	(0.009)
Chinese retaliation exposure		-0.000	0.001	0.001
		(0.002)	(0.003)	(0.003)
Control variables	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	3700	3700	3700	3700
Adjusted R-squared	0.101	0.261	0.101	0.100
Panel B: Diagnostics				
Dep. variable:	Chinese retaliation exposure	Chinese retaliatory tariffs	Chinese retaliatory tariffs	Chinese retaliatory tariff count
Specification	County	SIC4 level	SIC4 level	SIC2 level
Trump tariff exposure	2.987***			
	(0.337)			
Trump tariffs		1.127***	1.174***	
		(0.130)	(0.128)	
Trump tariff count				1.020***
				(0.046)
Control variables	Yes	n/a	n/a	n/a
Fixed effects	State	None	SIC2	None
Observations	3700	437	437	31
Adjusted R-squared	0.978	0.516	0.573	0.896

Panel A conducts previous regressions with both Trump tariff exposure and Chinese retaliation exposure included. The pervious 2SLS result (column (1) of Panel A, Table 4) is reproduced as column (1) of Panel A for the purpose of comparison. Chinese retaliation exposure rather than Trump tariff exposure is instrumented in column (4) of Panel A. In Panel B, China's retaliatory tariffs (various measures, including exposure and count) are regressed on Trump tariffs (various measures, including exposure and count), in order to understand the statistical insignificance in Panel A. See the text for details. Robust errors are clustered at the state level in Panel A and column (1) of Panel B. Robust errors are used in columns (2) to (4) of Panel B. *** p<0.01.

find the same effect on the heat levels and distribution. Taken together, at the root of the high correlation between the two exposures is the product structure of the US-China trade.

Because of the high correlation between the two exposure measures, the role of Chinese retaliation in the midterm elections cannot be uncovered in a reduced-form fashion: simply including $RetTariffExpo_c$ in the regression causes collinearity. We resort to a simple theoretical structure to tackle the role of China's retaliation in our estimation. Conceptually, our regression specification (2) identifies the sum of two effects of Trump tariffs at the county level:

$$\underbrace{\left(\frac{\partial[R_{c,2018} - R_{c,2016}]}{\partial TrumpTariffExpo_c}\right)}_{\hat{\alpha}_1^{OLS} \text{ and } \hat{\alpha}_1^{2SLS}} = \text{direct effect}_c + \text{indirect effect}_c \tag{9}$$

$$= \frac{\partial \Delta R_c}{\partial \Delta t_p^{Trump}} + \sum_{p' \in c} \underbrace{\frac{\partial \Delta R_c}{\partial \Delta t_{p'}^{China}}}_{\substack{\text{political feedback} \\ \text{to Chinese retaliation}}} \underbrace{\left(\sum_{p \in US} \frac{\partial \Delta t_{p'}^{China}}{\partial \Delta t_p^{Trump}}\right)}_{\substack{\text{Chinese retaliation} \\ \text{function}}}. \tag{10}$$

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 the Republicans. The "Chinese retaliation function" term in equation (10) 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'. The "political feedback to Chinese retaliation" term in the equation is the local political responses of local voters to the Republican Party, given the Chinese retaliatory tariff on 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 $\{p' \in c\}$.

Before proceeding to using structure (10) in estimation, it is noteworthy that this simple structure can illustrate why including both $TrumpTariffExpo_c$ and $RetTariffExpo_c$ in a regression causes collinearity in a two-country context. The effect of retaliatory tariff exposure is

$$\frac{\partial[R_{c,2018} - R_{c,2016}]}{\partial RetTariffExpo_c} = \sum_{p' \in c} \frac{\partial \Delta R_c}{\partial \Delta t_{p'}^{China}}. \tag{11}$$

Comparing equation (11) with equation (10), one can see that collinearity arises when the Chinese retaliation function in equation (10), namely $\partial \Delta t_{p'}^{China} / \partial \Delta t_p^{Trump}$ does not have much variation. For instance, if the derivative matrix of $\partial \Delta t_{p'}^{China} / \partial \Delta t_p^{Trump}$ is a diagonal matrix, the indirect effect in equation (10) will be another way of aggregating $\partial \Delta R_c / \partial \Delta t_{p'}^{China}$ across p' in the set $\{p' \in c\}$ and thus a linear transformation of equation (11), causing strong collinearity in the regression with both $TrumpTariffExpo_c$ and $RetTariffExpo_c$ as regressors.[24] The tariff structures of the two

[24] An extreme case makes the diagonal matrix issue even clearer: assuming the derivative matrix of $\partial \Delta t_{p'}^{China} / \partial \Delta t_p^{Trump}$ to be an identity matrix, then the indirect effect will be the same as $\frac{\partial[R_{c,2018} - R_{c,2016}]}{\partial RetTariffExpo_c}$.

countries, as shown by the two SIC panels of Figure 3, indeed resemble the diagonal pattern. Thus, in the US-China setting, collinearity arises easily to render the coefficients of both exposure measures statistically insignificant.[25]

To use structure (10) in estimation, we exclude all products that were included in China's retaliatory tariffs for each county c, which will turn off the indirect effect: the set $\{p' \in c\}$ in equation (10) is now made empty. By equation (10), excluding those products makes China's retaliation irrelevant to county c such that the estimated total effect contains only the direct effect. Results from the "retaliation-free" experiment, as reported in Table 10, confirm our previous findings. Since the sample of products unrelated to China's retaliatory tariffs reproduces our previous findings, the previously estimated pro-Republican effect of Trump's tariffs is unlikely to be a masked positive indirect effect stemming from China's retaliation (e.g., nationalism or patriotism, in favor of the current government or party in power). Thus, our interpretation of the previous results hold: Trump's tariffs have a pro-Republican impact independent from China's retaliation.

Lastly, we take a step back and make two notes. First, the retaliation-free experiment conducted here serves as a robustness check, the goal of which is to ascertain that the pro-Republican effect of Trump's tariff is not purely a positive indirect effect resulting from China's retaliation. We do not assume signs for the two effects and aim not to separately estimate the direct and indirect effects.[26] Second, theoretical structures are essentially assumptions imposed by researchers and the simple structure we use above is no exception. However, the results in Table 10 can also be interpreted without the structure—the Republican Party had smaller losses in counties that were exposed to elevated tariff protection while being less exposed to the retaliation. This reduced-form interpretation, although less revealing about the role of China's retaliation in the estimation, is still evident of the validity of the previous findings. With either estimation approach, Trump's tariffs garnered relatively more support for the Republicans in counties less affected by China's retaliation.

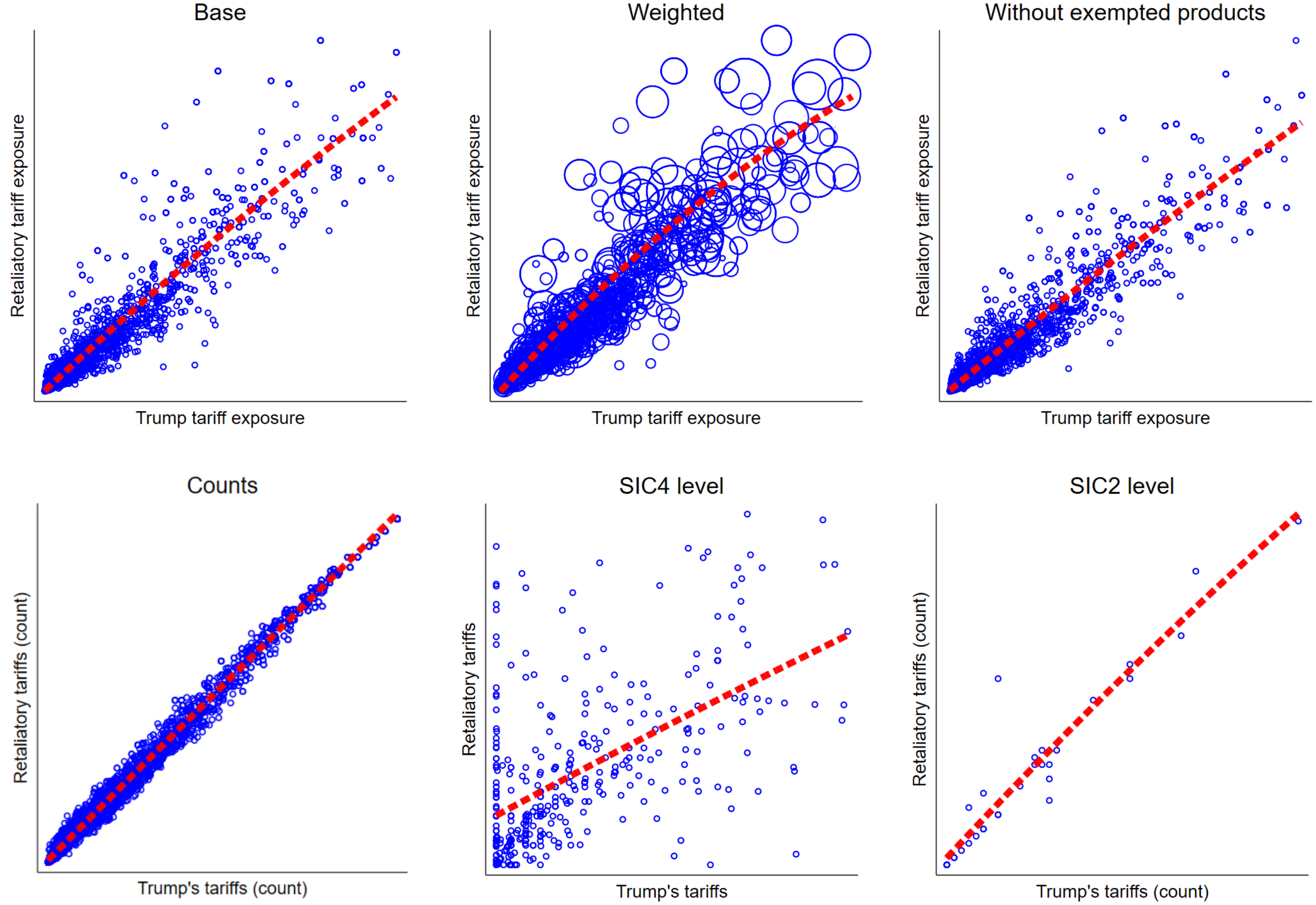
[25]When the exposure measure involves multiple countries, this collinearity becomes less likely because equation (11) now has another layer of summation:

$$\frac{\partial[R_{c,2018} - R_{c,2016}]}{\partial RetTariffExpo_c} = \sum_i \sum_{p' \in c} \frac{\partial \Delta R_c}{\partial \Delta t^i_{p'}},$$

where i indexes retaliating country i. Even if the Trump tariff exposure has the same summation across retaliating country i, the chance of having collinearity is low because the trade-war tariffs of the US and the retaliating countries have dissimilar product structures.

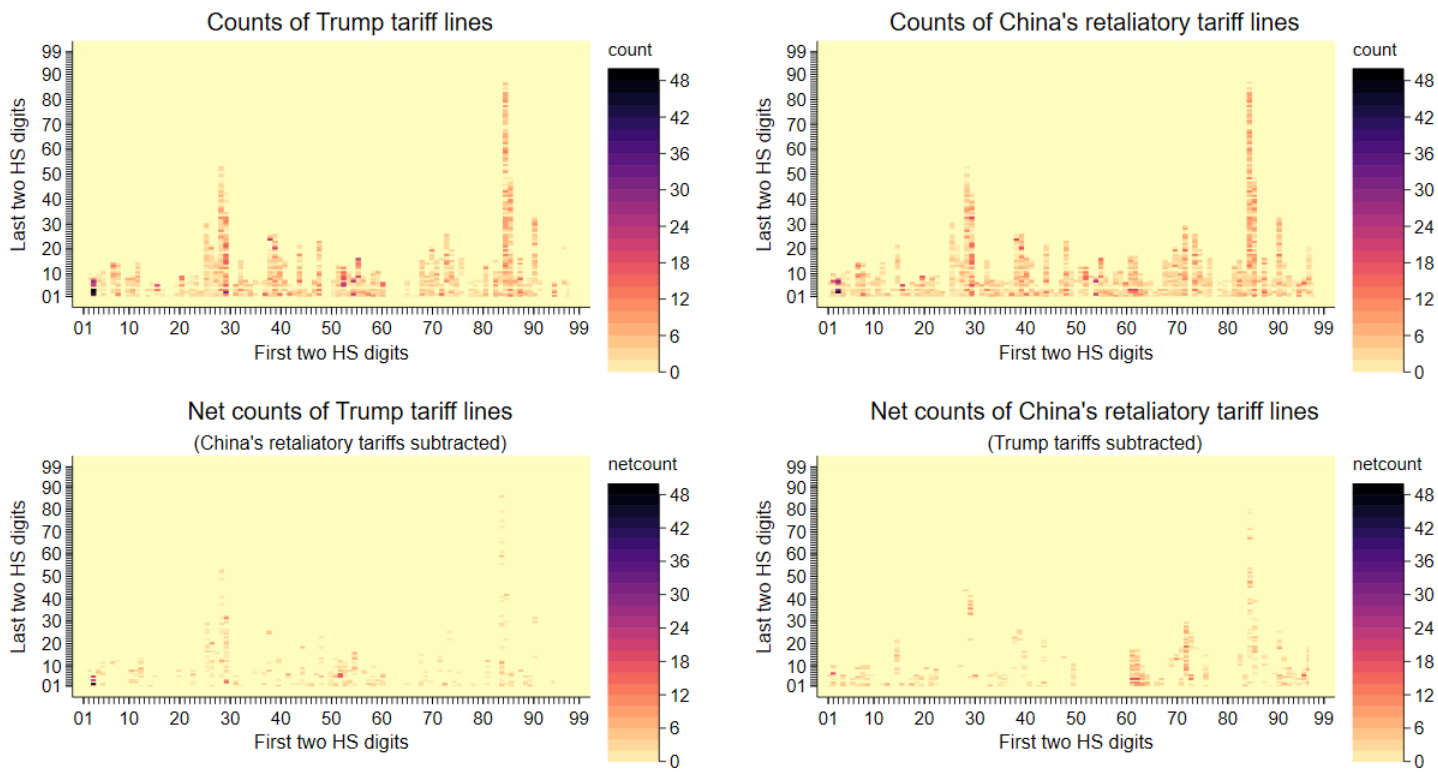
[26]The direct effect can be either positive (i.e., local voters reward the Republicans for the tariff protection) or negative (e.g., local voters penalize the Republicans for more costly imported inputs). The same applies to the indirect effect: local voters might blame the Republicans for China's retaliation (i.e., the indirect effect is negative) or blame China for its retaliation (i.e., the indirect effect is positive). Both the OLS- and 2SLS-coefficients are larger in magnitude than their counterparts in Tables 2 and 4. For the reason stated in the text, we refrain from interpreting it as removal of a negative indirect effect associated with the excluded effects. It could alternatively be interpreted as the removal of a negative direct effect associated with the excluded products.

Figure 3: China's Retaliatory Tariffs vs Trump's China tariffs



Tariff exposures (Trump's tariffs and China's retaliatory tariffs) are plotted in the three upper panels, tariff rates in the lower-middle panel, tariff-line counts in the lower-left and lower-right panels. The upper-middle panel has markers weighted by county-level number of votes. The upper-right panel drops the products exempted later (see Section 3.1). In lower-middle and lower-right panels, SIC4 (SIC2) stands for the four (two) digit level of the Standard Industrial Classifications (SIC) Code. In all panels, dashed red lines represent quadratic fits.

Figure 4: Trump's China Tariffs and China's Retaliatory Tariffs



In all 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). *Left-side two plots*: 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. *Right-side two plots*: same as the left-side two plots but for the Chinese side.

Table 10: 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<0.01.

4.4 Alternative Units of Analysis

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 shrinks to 435, including 241 Republican-incumbent districts and 194 Democratic-incumbent districts. The results are reported in column (1) of Table 11. Checking in the opposite fashion, we also exclude counties that were split across districts 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 strictly county-level view of the picture. The findings are reported in column (2) of the table. In column (3), we exclude the state of Pennsylvania, where the boundaries of congressional districts were significantly redrawn in 2018. In column (4), we exclude counties in districts where either the 2016 or 2018 house race was uncontested. All these columns produce results similar to those in Tables 2 and 4.

4.5 Trends in American Politics

Counties with relatively more support for the Republicans might ride on trends that were somehow correlated with the exposure to Trump's China tariffs. 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 regression specification (2) to the previous political cycle 2014-2016. 2014 and 2016 were both election years for the house, and 2016 was also the year when Trump was elected president. In this 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.[27]

Notice that there is now an intentional 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 designed to detect pre-trends. Suppose that there existed pro-Republican momenta in some 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.[28] The previously significant effects of Trump's China tariffs on the Republican vote shares all disappear. This finding confirms that pre-trends, if they do exist, cannot explain our main findings.

Political trends are complicated, driven by domestic and foreign policies and the interplay among them. We also conduct robustness checks related to other potential confounders. In Table A9, we control for policies related to healthcare reforms (the possibility that the Republicans repeal the Affordable Care Act) and state and local tax deductions (SALT) offered by the Trump administration and find our previous findings remain intact in magnitude and significance.[29] In Table A10, we control for the exposure to Trump's tariffs on countries other than China with the same construct as $TrumpTariffExpo_c$. Our previous findings also remain. This additional exposure measure does not have explanatory power unless it enters alone into the regression. In Table A11, we apply regression specification (2) to explain the change in Republican vote share in house elections between 2018 and 2020 and find that the exposure to Trump's tariffs has no impact. The 2020 house elections were driven by various significant topics in addition to the trade

[27] 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.

[28] 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).

[29] The change in health insurance coverage turns out to be negatively correlated with support for the Republicans, which is in line with the finding by Blanchard et al. (2024).

Table 11: Alternative Units of Analysis

	(1)	(2)	(3)	(4)
Dep. variable:	Difference in the Republican vote share (2018 minus 2016)			
Sample:	Congressional districts	Excluding counties split across districts	Excluding the state of Pennsylvania	Excluding uncontested districts†
Panel A: OLS results				
Trump tariff exposure	0.009**	0.007***	0.006***	0.007***
	(0.004)	(0.002)	(0.002)	(0.001)
Control variables	Yes	Yes	Yes	Yes
State FE	No	Yes	Yes	Yes
Observations	435	2678	3594	3287
Adjusted R-squared	0.033	0.172	0.265	0.366
Panel B: 2SLS results				
Second stage:				
Trump tariff exposure	0.009*	0.007**	0.007***	0.006***
	(0.005)	(0.003)	(0.002)	(0.002)
Control variables	Yes	Yes	Yes	Yes
State FE	No	Yes	Yes	Yes
Observations	435	2678	3594	3287
Adjusted R-squared	0.038	0.068	0.105	0.165
First stage:				
MIC2025	0.735***	71.176***	77.771***	78.297***
	(0.041)	(5.232)	(3.355)	(3.136)

The four columns use four different samples respectively, as indicated in the "Sample" row. 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<0.01.

† Uncontested districts in 2018 were Alabama 7th (Terri Sewell), Florida 10th (Val Demings), Florida 14th (Kathy Castor), Florida 20th (Alcee Hastings), Florida 21st (Lois Frankel), Florida 24th (Frederica Wilson), Georgia 5th (John Lewis), Mass. 1st (Richard Neal), Mass. 4th (Joe Kennedy III), Mass. 7th (Ayanna Pressley), Mass. 8th (Stephen Lynch), New York 5th (Gregory Meeks), New York 16th (Eliot Engel), North Carolina 3rd (Walter Jones), Pennsylvania 18th (Mike Doyle), Virginia 3rd (Bobby Scott), and Wisconsin 2nd (Mark Pocan).

Uncontested districts in 2016 were Alabama 1st (Bradley Byrne), Alabama 4th (Robert B. Aderholt), Alabama 7th (Terri A. Sewell), Arizona 3rd (Raúl Grijalva), Florida 24th (Frederica S. Wilson), Georgia 1st (Earl L. Carter), Georgia 9th (Doug Collins), Georgia 10th (Jody B. Hice), Georgia 13th (David Scott), Georgia 14th (Tom Graves), Illinois 3rd (Daniel Lipinski), Illinois 4th (Luis V. Gutierrez), Illinois 15th (John Shimkus), Illinois 16th (Adam Kinzinger), Kentucky 2nd (Brett Guthrie), Kentucky 5th (Harold Rogers), Mass. 2nd (James P. McGovern), Mass. 5th (Katherine M. Clark), Mass. 6th (Seth Moulton), Mass. 7th (Michael E. Capuano), Nebraska 3rd (Adrian Smith), Oklahoma 1st (Jim Bridenstine), Pennsylvania 3rd (Mike Kelly), Pennsylvania 13th (Brendan F. Boyle), Pennsylvania 18th (Tim Murphy), Texas 8th (Kevin Brady), Virginia 11th (Gerald E. Connolly), and Wisconsin 3rd (Ron Kind).

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<0.01.

war (especially the COVID-19 pandemic). We consider the absence of continual impact evidence of the absent confounding trends. That is, if the previously estimated effect of the trade war tariffs was spuriously driven by a hidden trend, the trend would be unlikely to disappear in a period of only two years.

Ethnicity may also play a role in American politics related to trade, as found in the literature (e.g., Autor et al., 2020; Pierce and Schott, 2020; Baccini and Weymouth, 2021). Motivated by this literature, we extend our study to examine how the political response to Trump's tariffs varies by ethnicity in Appendix A.5. Now we move on to conclude this study.

5 Concluding Remarks

The Republican Party lost many seats and 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 the 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)) and we confirm and quantify them.

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

Ben G. Li, Yi Lu, Pasquale Sgro, and Xing Xu

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A.1 Details of data

Trump's 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). Specific to the China tariffs, see https://ustr.gov/issue-areas/enforcement/section-301-investigations/section-301-china/300-billion-trade-action. On July 6, 2018, Tranche 1 took effect. On August 23, 2018, Tranche 2 took effect, with five product codes (eight-digit HS codes) exempted. The five product codes belong to alginic acid, splitting machines, containers, floating docks, and microtomes. On September 24, 2018, Tranche 3 took effect, with 297 product codes partially or fully exempted. The 297 products include some consumer electronics products (such as smart watches and bluetooth devices), some chemical inputs for manufactured goods, textiles and agriculture, some health and safety products (such as bicycle helmets), and some child safety furniture (such as car seats and playpens).

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.

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-related trade shock). 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 the 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 "the Republicans expected to win narrowly." Districts NY-11 and SC-1 in the list were lost by the 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 the 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.

CCES. The Cooperative Election Study (formerly the Cooperative Congressional Election Study, or CCES) data can be downloaded at https://cces.gov.harvard.edu.

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 May 19, 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 Counterfactual Analysis

The Republican Party lost its house majority in the 2018 midterm elections. Heading into the midterm, the 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, the Republicans filled 200 of these, while Democrats filled 235, equating to a net loss for the Republicans of 35 seats. As shown in Section 3, the China tariffs helped the Republicans at the midterm. In this section, we quantitatively assess how many of the seats won by the 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 outcome reported in this appendix is 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 received a larger share of the district's votes, namely if

$$Repub\_Share_d \equiv \frac{Repub\_Votes_d}{Total\_Votes_d} > Dem\_Share_d \equiv \frac{Dem\_Votes_d}{Total\_Votes_d}. \tag{A.1}$$

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 construct 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

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

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

$$\widetilde{Repub\_Share}_d \equiv \frac{\sum_{c \in d} \widetilde{R}_{c,2018} \times Total\_Votes_c}{Total\_Votes_d}. \tag{A.3}$$

The subscript $\{c \in d\}$ in equation (A.3) denotes all counties associated with congressional district d.[30] As counterparts of shares (A.2) and (A.3), we have counterfactual Democratic candidate vote shares at the county level:

$$\widetilde{D}_{c,2018} = D_{c,2018} + \hat{\alpha}_1^{2SLS} \times TrumpTariffExpo_c, \tag{A.4}$$

and at the district level:

$$\widetilde{Dem\_Share}_d \equiv \frac{\sum_{c \in d} \widetilde{D}_{c,2018} \times Total\_Votes_c}{Total\_Votes_d}. \tag{A.5}$$

The $D_{c,2018}$ in equation (A.4) is the share of votes received by Democratic house candidates in county c.[31]

[30] 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 (A.1) 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 (A.1) and therefore they counteract each other to mitigate potential double-counting.

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

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 11). The counterfactual share of the Republican candidate in district d is

$$\widetilde{Repub\_Share}_d \equiv R_{d,2018} - \hat{\alpha}_1^{2SLS} \times TrumpTariffExpo_d, \tag{A.6}$$

while the counterfactual Democratic vote share in district d is:

$$\widetilde{Dem\_Share}_d \equiv D_{d,2018} + \hat{\alpha}_1^{2SLS} \times TrumpTariffExpo_d. \tag{A.7}$$

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 Republican candidates, the counterfactual analysis is relevant only to the districts where Republican candidates won. In particular, the congressional districts where the Republicans might have lost are the places where Trump's China tariffs made a difference. We located the districts where the 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 conduct counterfactual analysis on those districts.[32]

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 A4 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 A5. Out of the nine districts flipped by the Republicans, one (North Carolina District 9) would not have flipped.[33] In both tables, the results between and within the two approaches are close and stable. Evidently, all else held equal, the Republicans would have performed worse without the tariffs.

A.4 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

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

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

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 April 18, 2017 that urges stricter and more selective H-1B visa approval in order to "ensure that H-1B visas are awarded to the most-skilled or highest-paid petition beneficiaries."[34] Although formal policy changes to the program were not made by the US Citizenship and Immigration Services (USCIS) until January 2019, an increase in denial rates and audit requests ("Requests for Evidence") came through in the year 2018. The denial rate for H-1B petitions rose to 15% in Fiscal Year 2018, up from 7% in Fiscal Year 2017.[35] Meanwhile, Trump, who had advocated for corporate tax cuts during his campaign, signed the Tax Cuts and Jobs Act (TCJA) in December 2017.[36] The TCJA was introduced by the Republicans and passed largely along party lines in both chambers of Congress. Effective January 1, 2018, the TCJA lowered the corporate tax rate from 35% to 21%, and reduced or removed certain business-related tax deductions and credits at the same time.

We collected data on both policy changes to ascertain whether our previous results can be explained by these two contemporaneous policy changes.[37] The H-1B (visa) approvals for each sector (two-digit NAICS code) can be downloaded from the USCIS website. We calculated the 2018-minus-2017 difference in the number of H-1B approvals to measure the H-1B policy change. Since H-1B applications and approvals are based on fiscal years (which run October 1 through September 30), the 2018 H-1B approvals had all been completed by the time of the midterm elections. As shown in Figure A2, 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 A2, 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

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

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

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

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

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 A7 and A8. The results resemble those we report in the main text.

A.5 Extension: Ethnicity

Economic and political responses varying by ethnicity have been identified in the extant studies on the "China Syndrome" of the US economy (e.g., Autor et al., 2020; Pierce and Schott, 2020; Baccini and Weymouth, 2021). Inspired by these studies, we expand our study to examine how political responses to Trump's tariffs vary by ethnicity. We hypothesize that the white ethnic group tends to support the Republicans because of Trump's trade policy change, all else held equal. We construct a dummy variable $\mathbb{1}[Q(PopShare_c^k) > q]$ 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 $\mathbb{1}[Q(PopShare_c^k) > q]$ indicates. By design, the information conveyed by the dummy variable increases with q. For instance, $PopShare_c^k > 10$ is far less informative than $PopShare_c^k > 90$ 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 the dummy variables and their interactions with $TrumpTariffExpo_c$ into the specification of column (1), Panel A of Table 4 (2SLS estimation). The results are reported in Panel A of Table A12. As shown, as q rises from 10 to 90, the coefficient of the interaction terms turns from negative to positive for the White group, whereas from positive to negative for the Black group. Only the interactions between $\mathbb{1}[Q(PopShare_c^{White}) > 90])$ and $TrumpTariffExpo_c$ and between $\mathbb{1}[Q(PopShare_c^{Black}) > 90]$ and $TrumpTariffExpo_c$ are statistically significant. The pattern is consistent with the relationship between the white ethnicity and trade liberalization in the literature—heavily exposed counties experience declines in manufacturing employment, a sector in which whites are disproportionately employed.

We then turn to the individual-level data. In Panel B, we use the voter-level data from the Cooperative Election Study (CCES). We keep the specification as close to Panel A as possible but use the voting for Republican indicator (0 or 1) as the dependent variable and replace the percentile dummies used in Panel A with individual ethnic type dummies. None of the interaction terms is statistically significant, as reported in Panel B. Notice that the statistical insignificance does not result from data quality or merge, as the uninteracted term $TrumpTariffExpo_c$ is statistically significant, confirming the association between supporting the Republicans and exposure to Trump's tariffs at the individual level.

Taken together, Table A12 indicates that county-level ethnic composition and individual-level ethnic type have different implications on how voters respond to trade policies. If a county has a high concentration of an ethnic group predominantly affected by a trade policy, the collective response can be more pronounced than the individual response. The magnified response might be driven by political representation (i.e., politicians advocate for protectionism to their advantage or to their competitors' disadvantage) or peer effects (i.e., individuals in the same ethnic group reinforce each other's political stance), which emerge only when the local ethnic group is large enough.

A.6 Additional Tables and Figures

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 shares	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	Exposure Variant 1	Exposure Variant 2	Exposure Variant 3
Trump tariff exposure	0.007***	0.081***	0.007***	0.301**
	(0.002)	(0.022)	(0.002)	(0.126)
Manufacturing share	-0.054	-0.052	-0.054	-0.070*
	(0.032)	(0.033)	(0.032)	(0.035)
Median wage (log)	7.248	7.045	7.185	6.137
	(7.369)	(7.411)	(7.376)	(6.275)
Labor participation rate	-0.206*	-0.205*	-0.206*	-0.142
	(0.118)	(0.120)	(0.119)	(0.126)
Unemployment rate	0.755**	0.744**	0.749**	0.647*
	(0.345)	(0.349)	(0.345)	(0.336)
Population (log)	-0.861	-0.779	-0.846	-0.836
	(0.934)	(0.961)	(0.936)	(0.705)
High school	0.707***	0.709***	0.706***	0.589**
	(0.210)	(0.209)	(0.211)	(0.225)
College degree	0.161	0.156	0.158	0.042
	(0.211)	(0.206)	(0.210)	(0.246)
Bachelor degree or higher	0.456*	0.458*	0.454*	0.328
	(0.264)	(0.259)	(0.264)	(0.300)
Black	0.027	0.029	0.027	0.010
	(0.114)	(0.114)	(0.114)	(0.114)
Asian	0.075	0.078	0.075	0.053
	(0.282)	(0.285)	(0.283)	(0.284)
Hispanic	0.107	0.105	0.107	0.108
	(0.102)	(0.101)	(0.102)	(0.117)
Male	-0.065	-0.044	-0.065	-0.116
	(0.428)	(0.434)	(0.429)	(0.369)
Evangelical Protestant	-1.067	-0.982	-1.054	0.181
	(9.352)	(9.442)	(9.360)	(10.129)
Mainline Protestant	-0.811	-0.921	-0.786	2.931
	(9.658)	(9.770)	(9.668)	(11.379)
Catholic	1.288	1.314	1.327	4.235
	(12.061)	(12.093)	(12.070)	(13.177)
Orthodox	59.766	59.622	59.794	55.477
	(79.613)	(79.988)	(79.657)	(76.433)
Black Protestant	2.732	2.151	2.778	6.329
	(22.047)	(22.123)	(22.089)	(23.058)
Female candidate (0 or 1)	0.079	0.080	0.079	0.090
	(0.373)	(0.374)	(0.374)	(0.372)
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	-2.056
	(22.666)	(22.447)	(22.662)	(26.960)
China-related trade shock	-0.060	-0.051	-0.058	-0.060
	(0.178)	(0.181)	(0.179)	(0.177)
Age group shares	Yes	Yes	Yes	Yes
Observations	3700	3700	3700	3700
Adjusted R-squared	0.262	0.261	0.261	0.258

Specifications are the same as in Table 2.

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 shares	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	Exposure Variant 1	Exposure Variant 2	Exposure Variant 3	MIC2025 as counts
Trump tariff exposure	0.006***	0.076***	0.006***	0.405***	0.007*
	(0.002)	(0.025)	(0.002)	(0.143)	(0.004)
Manufacturing share	-0.054*	-0.053	-0.054*	-0.073**	-0.054
	(0.032)	(0.032)	(0.032)	(0.034)	(0.033)
Median wage (log)	7.044	6.945	7.003	6.477	7.183
	(7.065)	(7.113)	(7.079)	(6.549)	(7.689)
Labor participation rate	-0.199*	-0.201*	-0.199*	-0.146	-0.206
	(0.112)	(0.112)	(0.112)	(0.125)	(0.143)
Unemployment rate	0.739**	0.736**	0.734**	0.668*	0.750**
	(0.328)	(0.328)	(0.328)	(0.350)	(0.370)
Population (log)	-0.728	-0.710	-0.725	-1.300	-0.849
	(0.805)	(0.805)	(0.805)	(0.910)	(1.181)
High school	0.697***	0.704***	0.697***	0.583**	0.706***
	(0.224)	(0.226)	(0.224)	(0.223)	(0.189)
College degree	0.143	0.146	0.142	0.065	0.159
	(0.227)	(0.226)	(0.226)	(0.236)	(0.203)
Bachelor degree or higher	0.439	0.449	0.439	0.342	0.454*
	(0.284)	(0.284)	(0.284)	(0.288)	(0.245)
Black	0.025	0.028	0.025	0.009	0.027
	(0.113)	(0.114)	(0.113)	(0.115)	(0.112)
Asian	0.076	0.079	0.076	0.042	0.075
	(0.286)	(0.287)	(0.286)	(0.266)	(0.282)
Hispanic	0.104	0.103	0.104	0.121	0.107
	(0.103)	(0.102)	(0.103)	(0.110)	(0.098)
Male	-0.053	-0.038	-0.054	-0.179	-0.066
	(0.407)	(0.410)	(0.407)	(0.393)	(0.458)
Evangelical Protestant	-0.410	-0.627	-0.452	-1.723	-1.064
	(9.106)	(9.048)	(9.105)	(9.387)	(9.847)
Mainline Protestant	0.094	-0.421	0.041	1.009	-0.796
	(9.263)	(9.148)	(9.263)	(10.607)	(11.199)
Catholic	2.039	1.723	2.013	2.584	1.320
	(11.922)	(11.901)	(11.932)	(12.454)	(11.709)
Orthodox	59.690	59.588	59.722	54.265	59.743
	(79.607)	(80.005)	(79.658)	(76.583)	(79.511)
Black Protestant	3.063	2.363	3.077	6.396	2.763
	(21.966)	(21.951)	(22.001)	(23.316)	(22.012)
Female candidate (0 or 1)	0.083	0.083	0.083	0.078	0.079
	(0.372)	(0.373)	(0.373)	(0.375)	(0.382)
Population density	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gini	-9.621	-10.645	-9.714	-4.295	-11.121
	(22.849)	(22.581)	(22.853)	(25.330)	(24.877)
China-related trade shock	-0.059	-0.051	-0.058	-0.064	-0.059
	(0.179)	(0.181)	(0.179)	(0.177)	(0.179)
Age group shares	Yes	Yes	Yes	Yes	Yes
Observations	3700	3700	3700	3700	3700
Adjusted R-squared	0.102	0.101	0.101	0.094	0.101
First stage :					
MIC2025	74.661***	6.155***	76.931***	77.206***	10.125***
	(3.820)	(0.269)	(3.573)	(3.561)	(0.833)

Specifications are the same as in Table 4.

Table A4: Counterfactual Analysis (Congressional Districts Narrowly Won by the 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 the 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. Coefficients and standard errors 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 11).

Table A5: Counterfactual Analysis (Congressional Districts Flipped by the 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 the 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. Coefficients and standard errors 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 11).

Table A6: Voter Turnout

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<0.01.

Table A7: 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 (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<0.01.

Table A8: Sector Heterogeneity Check II (Corporate 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 (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<0.01.

Table A9: Healthcare and Tax Reforms

	(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					
Trump tariff exposure	0.007***	0.006***	0.003	0.004**	0.008**
	(0.002)	(0.002)	(0.004)	(0.002)	(0.003)
Health insurance share†	0.346	-0.248	1.286	0.025	0.738
	(0.243)	(0.392)	(0.848)	(0.131)	(0.518)
Δ Health insurance share†	-0.709**	-0.093	-1.337	-0.389**	-1.031
	(0.289)	(0.312)	(1.068)	(0.169)	(0.699)
Amount per return (SALT)‡	-0.060	-0.177	0.104	-0.212***	0.001
	(0.057)	(0.118)	(0.205)	(0.050)	(0.119)
Observations	3556	913	722	2756	799
Adjusted R-squared	0.271	0.278	0.443	0.261	0.336
2SLS Results					
Trump tariff exposure	0.007***	0.007***	0.010**	0.002	0.010***
	(0.002)	(0.002)	(0.004)	(0.002)	(0.004)
Health insurance share†	0.342	-0.237	1.310	0.010	0.753
	(0.248)	(0.393)	(0.923)	(0.133)	(0.539)
Δ Health insurance share†	-0.699**	-0.101	-1.776	-0.385**	-1.088
	(0.304)	(0.314)	(1.362)	(0.171)	(0.761)
Amount per return (SALT)‡	-0.062	-0.163	-0.066	-0.234***	0.005
	(0.062)	(0.119)	(0.159)	(0.058)	(0.119)
Observations	3556	913	722	2756	799
Adjusted R-squared	0.113	0.249	0.318	0.099	0.192

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. Only key coefficients are reported. Control variables (same as in Tables 2 and 4) and state fixed effects are included. Robust errors are clustered at the state level. ** p<0.05, *** p<0.01.

† The construction of these two variables follows Blanchard et al. (2024). The data are from the American Community Survey. Health insurance share refers to the share of the population with health insurance just prior to the 2018 house elections (2013-2017 five-year averages, measuring how important the preservation of the Affordable Care Act (ACA) was perceived at the county level). Δ Health insurance share is the change in the share with health insurance in the years since the Affordable Care Act was passed (2013-2017 five-year averages − 2008-2012 five year averages, proxying for the share of the population whose health insurance coverage might be vulnerable if the ACA had been repealed).

‡ Amount per return is the mean SALT amounts per tax return filed at the county level. SALT stands for state and local taxes and the policy change refers to Trump administration's 2017 Tax Cuts and Jobs Act that introduced a cap of $10,000 per household on SALT deductions that could be claimed on federal tax returns.

Table A10: Trump's Tariffs Imposed on Other Countries

	(1)	(2)	(3)	(4)	(5)
Sample:	All	Red	Blue	Republican incumbent	Democratic incumbent
Dep. Variable is Republican vote share					
Panel A: Both exposures					
Trump China tariff exposure	0.008***	0.006**	-0.000	0.008**	0.011***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Trump other-country tariff exposure†	-0.007	0.017	0.012	-0.012	-0.014
	(0.010)	(0.016)	(0.009)	(0.014)	(0.015)
Observations	3700	1047	724	2888	811
Adjusted R-squared	0.262	0.274	0.413	0.249	0.325
Panel B: Other-country exposure only					
Trump other-country tariff exposure†	0.013**	0.046***	0.011*	0.007	0.009
	(0.005)	(0.011)	(0.006)	(0.008)	(0.010)
Observations	3700	1047	724	2888	811
Adjusted R-squared	0.250	0.269	0.414	0.236	0.309

All estimates are OLS estimates. 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. Only key coefficients are reported. Control variables (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<0.01.

† Trump other-country tariff exposure is constructed in the same fashion as the Trump China tariff exposure. The tariff rate on each product is equal to the total additional tariff rates across countries (excluding China). Results from using each of those foreign countries are highly similar to those in Panel A, and similar to Panel B to varying extent, depending on the country in focus (available upon request).

Table A11: House Elections 2020

	(1)	(2)	(3)	(4)	(5)
Dep. variable:	Republican vote share (2020 minus 2018)				
Sample:	All	Red	Blue	Republican incumbent	Democratic incumbent
OLS Results					
Trump tariff exposure	-0.000	-0.003**	0.001	0.002	0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Observations	3086	953	477	2647	614
Adjusted R-squared	0.216	0.424	0.181	0.266	0.274
2SLS Results					
Trump tariff exposure	-0.002	-0.002	-0.002	0.001	-0.001
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Observations	3086	953	477	2647	614
Adjusted R-squared	0.054	0.203	0.104	0.078	0.091

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. Only key coefficients are reported. Control variables (same as in Tables 2 and 4) and state fixed effects are included. Robust errors are clustered at the state level. ** $p<0.05$.

Table A12: The Role of Ethnicity

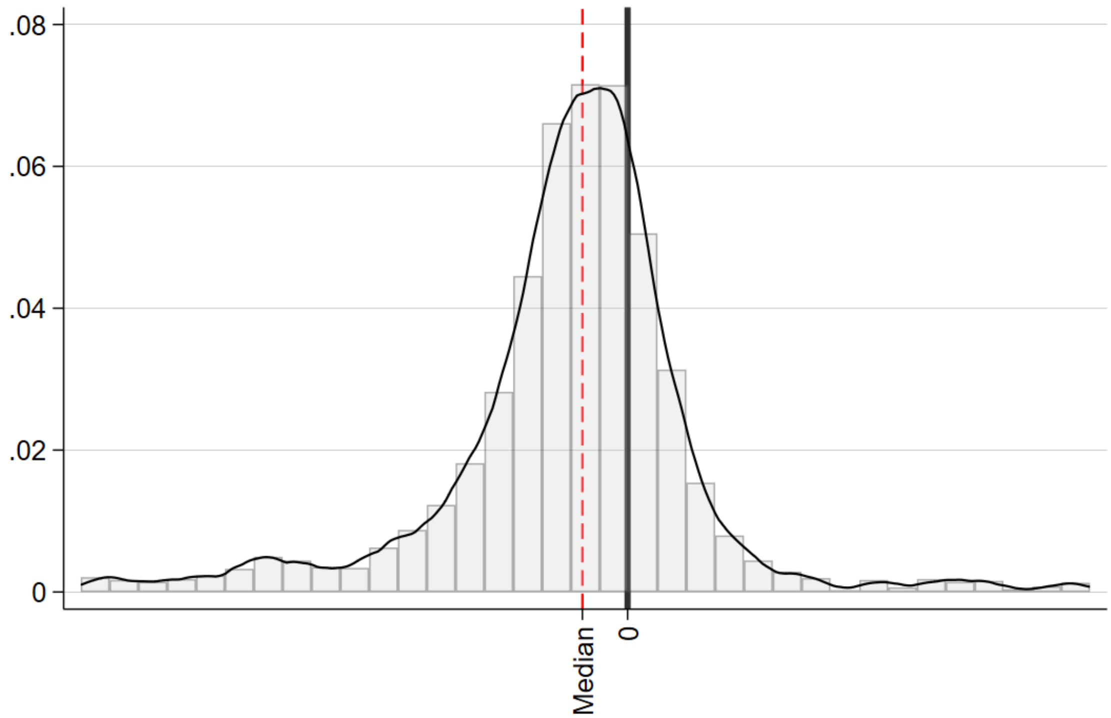
	(1)	(2)	(3)	(4)
Panel A; County level results †				
Dep. variable:	Difference in the Republican vote share			
Trump tariff exposure	-0.239	-0.053	-0.093	-0.118
	(0.192)	(0.079)	(0.096)	(0.076)
	q=10	*q=25*	*q=75*	*q=90*
Trump tariff exposure × Dummy (White pop. share, percentile > *q*)	-0.002	-0.009	0.099	0.134*
	(0.006)	(0.026)	(0.081)	(0.072)
Trump tariff exposure × Dummy (Black pop. share, percentile > *q*)	0.098	-0.050	-0.003	-0.047**
	(0.166)	(0.050)	(0.003)	(0.021)
Trump tariff exposure × Dummy (Hispanic pop. share, percentile > *q*)	0.149*	0.118***	0.002	-0.011
	(0.086)	(0.034)	(0.025)	(0.010)
Observations	3700	3700	3700	3700
Adjusted R-squared	0.108	0.138	0.110	0.128
Panel B: Individual level results ‡				
Dep. variable:	Voting for Republicans Indicator (0 or 1)			
Trump tariff exposure	0.012***			
	(0.004)			
Trump tariff exposure × Dummy (White)	0.002			
	(0.002)			
Trump tariff exposure × Dummy (Black)	0.001			
	(0.003)			
Trump tariff exposure × Dummy (Hispanic)	0.001			
	(0.002)			
Observations	38998			
Adjusted R-squared	0.210			

Asian is the reference group. Only the Trump tariff exposure measure and its interaction terms are reported to save space. Other terms (including uninteracted ethnicity dummies) are not reported. Robust errors are clustered at the state level. * p<0.10, ** p<0.05, *** p<0.01.

† Panel A presents 2SLS results from the sample of column (1), Panel A of Table 4. For each ethnic group among White, Black, and Hispanic, an ethnicity dummy variable is created representing the population share of the ethnicity is above the q percentile across counties. From column (1) to (4) in the panel, q rises so that the dummy variable indicates a larger concentration of the ethnicity in focus. These dummies are inserted into regressions uninteracted and interacted with Trump tariff exposure. All other specifications remain the same as those of column (1), Panel A of Table 4.

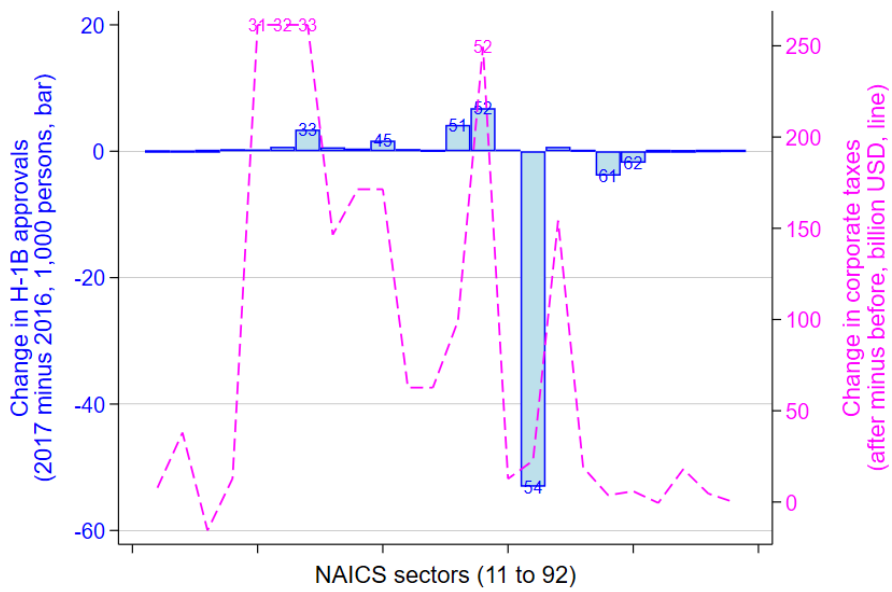
‡ Panel B presents 2SLS results from individual level data from the Cooperative Election Study (CCES). The specification is similar to column (1), Panel A of Table 4, but uses the voting for Republican indicator (=1) or not (=0) as the dependent variable. Regressions use interacted ethnicity dummy terms as in Panel A, where the ethnicity dummies are at the individual level. Control variables include those used in Panel A and individual level controls: income dummies (10K-20K, 20K-30K, 30K-40K, 40K-50K, 50K-60K, 60K-70K, 70K-80K, 80K-100K, 100K-120K, 120K-150K, 150K+), employment status dummies (part-time, temporarily laid off, unemployed, retired, permanently disabled, homemaker, student), education level dummies (high school graduate, some college, 2-year, 4-year, post-graduate), female dummy, age variable, and religion dummies (Roman Catholic, Mormon, Eastern or Greek Orthodox, Jewish, Muslim, Buddhist, Hindu, Atheist, Agnostic, nothing particular).

Figure A1: Distribution of the Changes in the Republican Vote Share



Histogram of the changes in Republican vote share (2018 minus 2016) is displayed with kernel density. Median and zero value of the variable are marked in the figure. The mean is −3.26 percentage points and the 75th percentile is 0.30 percentage points.

Figure A2: 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