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ABSTRACT

We find that Republican candidates lost support in the 2018 congressional election in counties more exposed to trade retaliation, but saw no commensurate electoral gains from US tariff protection. The electoral losses were driven by retaliatory tariffs on agricultural products, and were only partially mitigated by the US agricultural subsidies announced in summer 2018. Republicans also fared worse in counties that had seen recent gains in health insurance coverage, affirming the importance of health care as an election issue. A counterfactual calculation suggests that the trade war (respectively, health care) can account for five (eight) of Republicans' lost House seats.

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1 Introduction

In early 2018, President Donald Trump launched a series of unprecedented actions to raise tariffs against major US trading partners. By September 2018, newly-introduced duties covered over 12% of US imports (Bown 2019). These tariffs were met with swift retaliation against US exports, especially on agricultural products, by China, Canada, the European Union, Mexico, and others.[1] While new US tariffs offered some protection for certain import-competing industries, retaliatory tariffs hurt other US producers. The export-dependent agricultural sector was especially hard-hit, prompting the Trump administration to announce a $12-billion subsidy program in summer 2018.

These trade-related events were exceptional in scope and scale, and by the eve of the November 2018 midterm elections, the potential repercussions of the trade war were widely publicized in both national and local media. But did voters care? This paper maps the geographic distribution of exposure to the 2018 trade war, including the subsequent agricultural subsidies, and evaluates whether this exposure varied systematically with voting patterns in the 2018 elections for the US House of Representatives.

We measure the extent to which US counties were protected by new US tariffs, the extent to which they were hit by retaliatory tariffs, and the degree to which they stood to benefit from agricultural subsidies extended under the 2018 Market Facilitation Program (MFP). Given the central role of health care policy in 2018 election rhetoric, we control for the extent of local health insurance coverage potentially vulnerable to repeal of the Affordable Care Act (ACA). We combine these key explanatory variables with a rich set of demographic and economic covariates to examine the relationship between voting patterns and county-level policy exposure.

The evidence reveals a modest but robust negative relationship between local employment exposure to the 2018 trade war and support for Republican House candidates. Republican candidates lost ground in counties that were adversely affected by retaliatory tariffs, but saw no discernable gains in counties where workers were disproportionately protected by new US tariffs. The negative relationship between retaliatory tariffs and Republican support was concentrated in politically competitive counties where Trump narrowly lost the popular vote in 2016, and in counties hardest hit by retaliatory tariffs on agricultural products, particularly those imposed by China. The 2018 agricultural subsidies only partially mitigated this negative relationship, although this offset was substantial in counties receiving the largest MFP payments. We also find that Republican support fell systematically in counties where recent increases in health insurance coverage had been greatest, underscoring how health care policy worked against Republican House candidates as an election issue.

Quantitatively, our regression estimates suggest that the trade war can account for roughly one-tenth of the observed nation-wide decline in Republican House candidates' vote share between 2016 and 2018. In comparison, the role of health care policy accounts for about one-fifth of the decline in

[1] Bown and Kolb (2019) offer a comprehensive timeline.

Republican support at the national level. Focusing on politically competitive counties, the estimated effect of retaliatory tariffs is substantially stronger and quantitatively commensurate to that of health care, with each force large enough to account for one-quarter of the decline in Republican support in these counties. The trade war and health care thus appear to have hurt Republican candidates where swing voters matter most.

We also translate our regression results into counterfactual Congressional election outcomes. Mindful of the complex US electoral geography, we consider several alternatives to apportion estimated county-level vote changes to congressional districts (CDs). The resulting predictions suggest that voters' response to the trade war could account for Republicans' (net) loss of five House seats in 2018, while concerns over health care coverage may have cost eight House seats. These findings suggest that both the trade war and health care policy contributed meaningfully to the 2018 'Blue Wave', in which Republicans lost a total of 40 House seats.

Our study builds on earlier work examining how economic openness, particularly US-China trade, impacts US domestic politics. Autor, Dorn, Hanson, and Majlesi (2017) and Che, Lu, Pierce, Schott, and Tao (2016) examine how the mid-2000s Chinese import surge (the 'China Shock') affected political polarization and voting. Following these papers, we adopt a shift-share approach – combining product-level tariffs with information on counties' initial industry employment mix – to measure local tariff exposure. We stop short of claiming causal identification, however. Although a county's employment composition is plausibly pre-determined, the 2018 tariffs were not orthogonal to future US political considerations: Fajgelbaum, Goldberg, Kennedy, and Khandelwal (2019) and Fetzer and Schwarz (2019) find that the geographic incidence of the 2018 tariffs is correlated with Republicans' prior election performance. Our exercise therefore should be understood as an *ex-post* evaluation of the extent to which the tariffs may have influenced the 2018 House elections.

Our work is also related to the mounting evidence that US consumers have borne the brunt of higher prices from the new US tariffs (Amiti, Redding, and Weinstein (2019), Cavallo, Neiman, Gopinath, and Tang (2019), Flaaen, Hortacsu, and Tintelnot (2019), Waugh (2019)). Our complementary research highlights potential consequences of *producer-side* exposure to the trade war via the local employment composition of US counties. To the extent that voters also responded politically to the consumer-side impact of tariffs, or even the broader rhetorical influence of the trade war (Mansfield and Mutz 2009), these additional responses will be captured (to an extent) by state fixed effects in our empirical specifications. Our findings therefore may constitute a lower bound for the overall political impact of the trade war.

Two related papers touch on the relationship between the trade war and the 2018 elections. Fetzer and Schwarz (2019) briefly assess whether the trade shock influenced voting outcomes, and Chyzh and Urbatsch (2019) find a systematic pattern of Republican electoral losses in counties that produce more soybeans. Our results are consistent with these papers, but we are the first (as far as we know) to find evidence of disproportionate political responses in politically competitive counties, and to demonstrate the influence of agricultural subsidies and health insurance for voting patterns. Our approach also allows us to characterize the consequences of the trade war in terms of both the Republican vote share and the number of seats lost.

2 Data

2.1 Elections

We adopt counties as the unit of analysis, this being the most disaggregated geographic unit with readily-available voting and socioeconomic data. The voting data are from David Leip's US Election Atlas. For each of the 2012-2018 US House elections and the 2016 Presidential election, we construct the county-level vote share received by Republican candidates.[2] Our sample comprises all US counties outside Alaska, which does not report county-level election returns. While the majority of counties – 2,633 out of 3,011 in our sample – are located within a single congressional district (CD), some counties are split across multiple CDs; we return to the implications of these 'splits' later.

Panel A of Table 1 reports summary statistics on these voting outcomes. Across counties, Republican House candidates lost 6.4 percentage points of vote share on average between 2016 and 2018. These losses unwound the Republicans' gains from the 2014-2016 and 2012-2014 election cycles, of 3.5 and 2.3 percentage points respectively. These changes exhibit considerable variation across counties: Republican candidates lost over 22 percentage points in the bottom decile of counties but gained nearly 3 percentage points in the top decile.

We further group the counties into six quantiles according to voting outcomes in the 2016 *Presidential* election, to capture how competitive the electoral landscape was leading into the 2018 midterms. Specifically, we bin the counties according to whether Trump garnered less than 30%, 30-40%, 40-50%, 50-60%, 60-70%, or over 70% of the vote. Panel C of Table 1 provides summary statistics for each "competitiveness bin". The total US population is divided roughly evenly across the six quantiles, except for the 40-50% bin, which is larger. Notice that the average population falls systematically across quantiles, reflecting the well-known pattern of stronger Republican support in less densely-populated areas.

2.2 The 2018 Trade Shock

Our county-level measures of the 2018 trade shock capture voters' potential tariff exposure through the industry composition of local employment. We construct: (i) the *US Tariff Shock*, defined as a county's average per-worker exposure to the increase in US tariffs on imports; and (ii) the *Retaliatory*

[2] We compute the 'two-party vote share', defined as the number of Republican votes divided by the total votes for Republican and Democratic candidates. We limit our attention to the 2018 House races, since Senate elections take place on a six-year cycle that would lead to a non-representative panel across states.

Table 1: Cross-County Summary Statistics

	Mean	Std. Dev.	10th pct.	50th pct.	90th pct.
A: Voting outcomes					
Republican House vote share (2018)	0.629	0.191	0.376	0.661	0.835
Republican House vote share (2016)	0.692	0.221	0.404	0.712	1.000
Δ Republican House vote share (2018 minus 2016)	-0.064	0.125	-0.224	-0.043	0.026
Δ Republican House vote share (2016 minus 2014)	0.035	0.148	-0.078	0.015	0.219
Δ Republican House vote share (2014 minus 2012)	0.023	0.137	-0.112	0.035	0.130
Republican Presidential vote share (2016)	0.667	0.161	0.435	0.701	0.845
B: Tariff shocks and other explanatory variables					
US Tariff Shock	0.219	0.370	0.012	0.106	0.506
… on Agricultural products	0.003	0.017	0.000	0.000	0.005
… on non-Agricultural products	0.216	0.370	0.009	0.104	0.505
Retaliatory Tariff Shock	0.166	0.294	0.019	0.094	0.335
… on Agricultural products	0.075	0.273	0.000	0.007	0.174
… of which, levied by China	0.074	0.267	0.000	0.007	0.170
… of which, levied by Canada, Mexico, EU	0.002	0.007	0.000	0.000	0.004
… on non-Agricultural products	0.091	0.115	0.008	0.058	0.205
… of which, levied by China	0.059	0.084	0.005	0.036	0.129
… of which, levied by Canada, Mexico, EU	0.032	0.056	0.002	0.017	0.075
Estimated Ag. subsidy per worker (2018)	0.429	1.080	0.000	0.027	1.345
Health insurance share (2013-17 avg.)	0.889	0.051	0.823	0.897	0.945
Δ Health insurance share (2013-17 minus 2008-12)	0.040	0.031	0.008	0.038	0.076
Total population (2016)	103,348	332,515	5,178	25,873	209,267

C: Counties by electoral competitiveness

By Republican vote share (2016 Pres.)	Number of counties	Avg. pop. (2016)	Total pop. (2016)	US Tariff Shock	Retaliatory Tariff Shock	Ag. subsidy per worker
$\mathbf{1}(\text{Pres. vote} \in [0, 0.3])$	98	559,293	54,810,720	0.111	0.131	0.084
				(0.136)	(0.436)	(0.292)
$\mathbf{1}(\text{Pres. vote} \in (0.3, 0.4])$	148	332,467	49,205,044	0.148	0.103	0.124
				(0.160)	(0.165)	(0.473)
$\mathbf{1}(\text{Pres. vote} \in (0.4, 0.5])$	243	299,096	72,680,235	0.188	0.121	0.127
				(0.196)	(0.180)	(0.531)
$\mathbf{1}(\text{Pres. vote} \in (0.5, 0.6])$	395	132,167	52,205,954	0.242	0.160	0.205
				(0.302)	(0.227)	(0.666)
$\mathbf{1}(\text{Pres. vote} \in (0.6, 0.7])$	665	71,730	47,700,374	0.269	0.163	0.350
				(0.449)	(0.254)	(0.833)
$\mathbf{1}(\text{Pres. vote} \in (0.7, 1])$	1,559	28,610	44,603,198	0.209	0.184	0.617
				(0.389)	(0.333)	(1.329)

Notes: Summary statistics across $N = 3,108$ counties, excluding Alaska. Voting outcomes in Panel A are from the Election Atlas; the Republican vote share is the number of votes for the Republican candidate out of total votes cast for the Democrat and Republican candidates. For Panel B, the US Tariff Shock, Retaliatory Tariff Shock, and agricultural subsidy measures are each in units of $1,000 per worker. The share of the civilian non-institutionalized population with health insurance is from the American Community Survey (five-year average series). The total county population data in 2016 are from the US Census resident population estimates. Panel C provides descriptive statistics on counties by electoral competitiveness bins, based on the Republican vote share in the 2016 Presidential election. For each bin, we report the number of counties, average population per county, total population across all counties, mean US Tariff Shock, mean Retaliatory Tariff Shock, and mean estimated Ag. subsidy per worker. Note that the total population is reported as a count variable. The standard deviations of the two tariff shock variables and the Ag. subsidy variable are reported in parentheses.

Tariff Shock, defined as the corresponding per-worker exposure to the retaliatory tariffs against US exports.

We briefly describe the construction of these two Tariff Shock variables here; further details are in the Appendix. We use HS 8-digit product-level data collected by Bown (2019) to identify tariff increases that had come into force by October 2018. The US Tariff Shock incorporates the tariff actions against washers and solar panels (Section 201), steel and aluminum (Section 232), and a broad swathe of imports from China (Section 301).[3] The Retaliatory Tariff Shock comprises the tariff responses by the US' four largest trading partners, Canada, Mexico, China, and the EU. To construct each Tariff Shock, we multiply the tariff rate increase by initial bilateral trade values, which we then concord to NAICS 3-digit industries. This yields measures of the tariff change in dollar terms in industry i, for US imports from country o, $TS_i^{o,US}$, and for US exports to country d, $TS_i^{US,d}$. We then map these industry-i tariff shocks to individual counties, indexed by c, by apportioning the national-level shock according to each county's share of national employment in industry i, $\frac{L_{i,c}}{L_i}$, taken from the 2016 US County Business Patterns. The final step aggregates the tariff shocks experienced by each county across industries and trading partners, and divides by total county population between ages 15-64, $\bar{L}_c$. This yields our US and Retaliatory Tariff Shock measures, in dollars per worker:

$$
\begin{aligned}
TS_c^{US} &= \sum_o \sum_i \frac{L_{i,c}}{L_i} \frac{TS_i^{o,US}}{\bar{L}_c}, \text{ and} && (1) \\
TS_c^{R} &= \sum_d \sum_i \frac{L_{i,c}}{L_i} \frac{TS_i^{US,d}}{\bar{L}_c}. && (2)
\end{aligned}
$$

The above measures focus on counties' tariff exposure through local employment that is directly affected. To the extent that local labor market outcomes were among voters' relevant concerns in the 2018 election, we would expect a decline in Republican vote share in counties more exposed to the Retaliatory Tariff Shock, all else equal.[4] Conversely, to the extent that new US tariffs protected American workers from foreign competition, as was the Trump administration's stated intention, we might expect Republican voter support to be positively correlated with the US Tariff Shock. We readily acknowledge that these simple predictions may be offset by other channels: higher US tariffs impose costs on consumers, as well as on downstream, using-industries; or conversely, voters may be willing to bear with retaliatory tariffs if they believe the trade war will eventually give the US leverage to improve market access or intellectual property protection. Such forces, if pertinent to voters and correlated with county employment, would generally bias the estimated political effects

[3] These include the initial July-August 2018 round of tariffs on \$50 billion of US imports from China, and the September 2018 round on an additional \$200 billion of US imports.

[4] Scheve and Slaughter (2001), Mayda and Rodrik (2005), and Fordham and Kleinberg (2012) find that voters' economic self-interest shapes their preferences over trade policy.

of TS_c^{US} and TS_c^R towards zero.

Table 1 reports summary statistics for the US and Retaliatory Tariff Shocks across counties. On average, the county-level producer-side exposure to the US tariffs was \$219 per worker, higher than the retaliatory tariff exposure at \$166 per worker. An advantage of TS_c^{US} and TS_c^R as constructed is that each can be decomposed additively into the tariff shocks by product and by partner country. Table 1 confirms that the bulk of US import protection covered non-agricultural (manufacturing) goods. The retaliatory tariffs were more evenly balanced between agricultural and non-agricultural products; in particular, retaliation on agricultural products came primarily from China.

Note further that the Retaliatory Tariff Shock is increasing modestly across the political competitiveness bins, as ordered by the 2016 Republican Presidential vote share (Table 1, Panel C). On the other hand, the US Tariff Shock exhibits a non-monotonic relationship with 2016 voting patterns that peaks in the 60-70% bin. These broad patterns are also documented in Fajgelbaum, Goldberg, Kennedy, and Khandelwal (2019) and Fetzer and Schwarz (2019) using different definitions of the tariff shock measures.[5] The focus of our paper is not to explain these county-level tariff shocks, however, but to evaluate their consequences for voting outcomes in the 2018 House elections.

Figure 1 maps the US Tariff Shock (Panel A) and the Retaliatory Tariff Shock (Panel B) across counties. These shocks do not overlap neatly, though they are positively correlated (correlation coefficient: 0.22). Both shocks exhibit considerable variation across the US geography, with a handful of counties receiving either a disproportionate amount of US tariff protection or costly tariff retaliation.

2.3 Agricultural Subsidies

In summer 2018, the US government announced a Market Facilitation Program (MFP) designed to mitigate the negative consequences of retaliatory tariffs for US farmers. Administered by the US Department of Agriculture, the program consisted of roughly \$12 billion in subsidies to be paid to farmers growing soybeans, sorghum, corn, wheat, and several other products adversely affected by new foreign tariffs. To construct estimates of the total MFP subsidies received in 2018 at the county level, we combine the announced subsidy rates for key commodities with information on production or inventory from preceding years. (See the Appendix for the full list of commodities included and data sources.) We construct the variable $AgSubs_c$ as the estimated total subsidy received by each county c, divided by its working-age population.

These MFP subsidies were narrowly distributed. Across counties, the mean per-worker subsidy was \$429, while the median value was \$27 (Table 1, Panel B); the largest beneficiaries were moreover rural, Republican counties (Panel C). Figure 1 illustrates the limited geographic scope of the program,

[5] Similar to Fajgelbaum, Goldberg, Kennedy, and Khandelwal (2019), we recover an 'inverted U-shape' when regressing our TS_c^{US} measure flexibly against a set of dummies for the competitiveness bins, although the coefficients are not always statistically significant. Likewise, we obtain an upward sloping relationship when regressing TS_c^R on the set of competitiveness bin dummies. (See Table A.6 in the Appendix.)

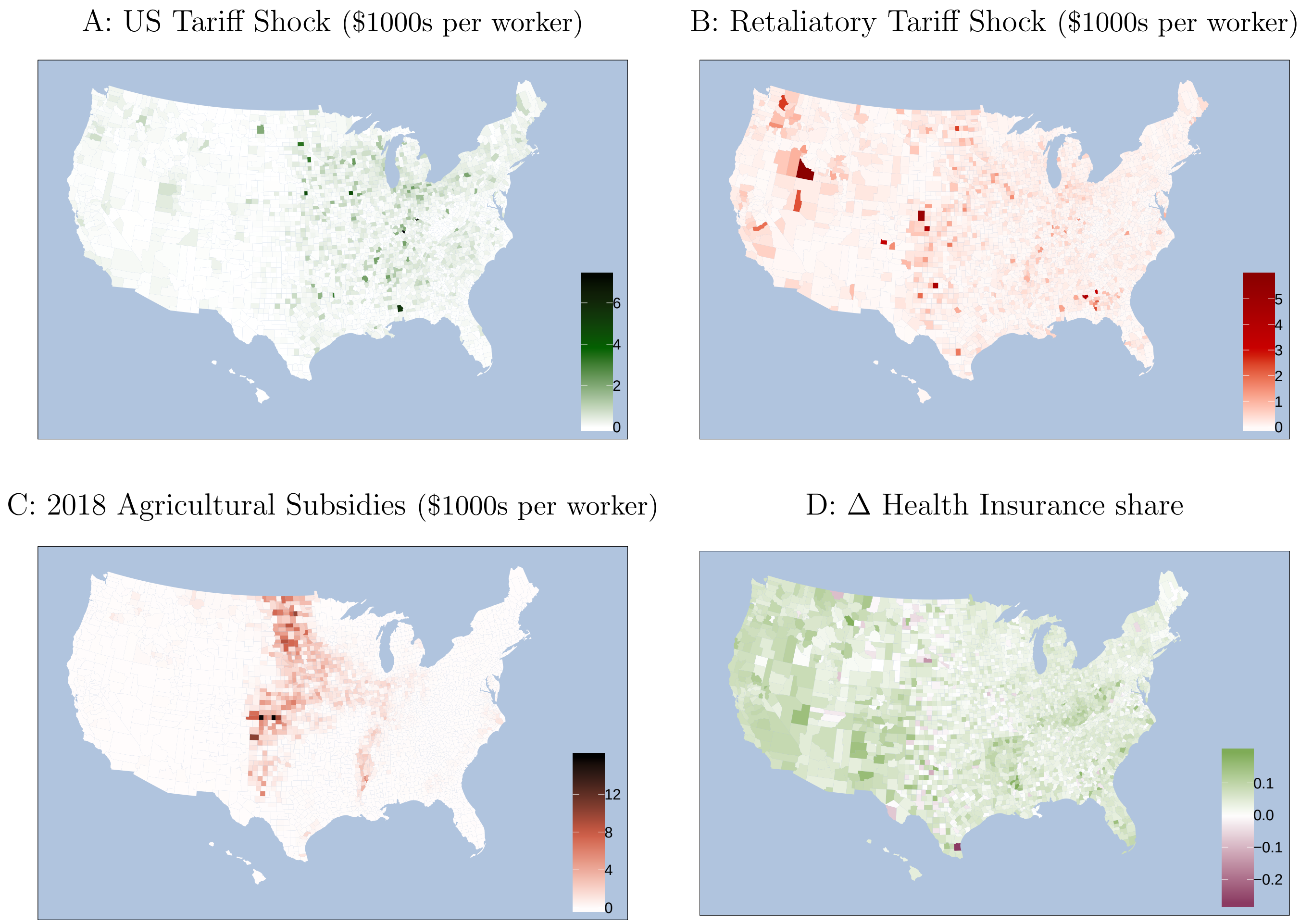

Figure 1

with the main recipients located in the plains and central states (Panel C).[6]

2.4 Health Care

The potential overhaul of US federal health care policy was a central issue in many Congressional campaigns in 2018 (e.g., Lowrey (2018)). In early 2017, the Republican House leadership began to introduce controversial legislation that would have repealed the Affordable Care Act (ACA), or 'Obamacare'. Although the efforts were ultimately thwarted in the Senate by the late John McCain's deciding vote in July 2018, health care remained a galvanizing campaign issue in November 2018. Preserving access to health insurance was particularly important for Democratic-leaning voters according to survey data (Blendon, Benson, and McMurtry 2018), while health care policy dominated Democratic campaign advertising in October 2018 (Wesleyan Institute for Advertising Research

[6]The cross-county correlation between the MFP subsidy per worker and the Retaliatory Tariff Shock is a modest 0.19. This is likely because more products were targeted by tariff retaliation than the Trump administration made eligible for subsidies. Even within agriculture, the tariff retaliation had a broader reach, since the MFP omitted most fruits, nuts and fishery products.

2018).

We thus include two county-level variables from the American Community Survey (ACS) in our analysis: the share of the population with health insurance just prior to the 2018 elections, and the change in the share with health insurance in the years since the ACA was enacted in 2010.[7] The first variable accommodates the possibility that counties with high rates of health care coverage may have seen preservation of the ACA as politically less important. The second variable proxies for changes in health insurance coverage since the ACA came into effect; following Hollingsworth, Sonil, Carroll, Cawley, and Simon (2019), we expect greater gains on this front to be negatively correlated with support for Republican House candidates in 2018.

County-level health insurance rates rose on average by roughly 4 percentage points in the five years since the ACA was enacted (Table 1, Panel B).[8] The gain was below 1 percentage point for the 10th percentile county, but nearly 8 percentage points at the 90th percentile. Panel D of Figure 1 confirms that the increases in health insurance coverage were spread across the United States; the geographic distributions of the tariff shocks and (especially) the 2018 agricultural subsidies were more narrow in comparison (Panels A-C).

2.5 Other Control Variables

We include a broad set of county-level demographic and socioeconomic covariates, guided by the considerable empirical literature on determinants of electoral outcomes.[9] To control for demographics, we include population shares by age group, gender, and race, from the US Census. To control for differences in economic composition across counties, we include employment shares by sector (agriculture, mining, manufacturing), from the County Business Patterns dataset. We also include the unemployment rate, (log) mean household income, and share of the population with a college degree, from the American Community Survey. For all of these variables, we include both pre-election levels and pre-trends as controls. Construction of these variables is detailed in the Appendix, with summary statistics reported in Table A.1.

[7]We use respectively the ACS 5-year average between 2013-2017 (to reduce potential noise in yearly reporting), as well as the difference between the 2013-2017 average and the 2008-2012 average.

[8]This figure is comparable to the CBO (2017) estimate for the number of Americans – 17 million – that would no longer have held health insurance in 2018 had the repeal legislation passed.

[9]Theiss-Morse, Wagner, Flanigan, and Zingale (2018) and Kondik (2019) provide detailed treatments. Shafer and Wagner (2018) argue that the fundamental drivers of US voting patterns were largely unchanged in the 2018 election.

3 Empirical Model

Our baseline regression specification is:

$$\begin{aligned}\Delta RVoteSh_c^{18,16} &= \beta_1 TS_c^{US} + \beta_2 TS_c^{R} + \alpha_1 AgSubs_c \times TS_c^{R} + \alpha_2 AgSubs_c + \delta HInsur_c \\ &\quad + \eta R_c + \gamma RVoteSh_c^{P16} + \Gamma X_c + D_s + \epsilon_c. \end{aligned} \tag{3}$$

The dependent variable $\Delta RVoteSh_c^{18,16}$ is the 2018 Republican House vote share in county c minus the corresponding share in the 2016 election. TS_c^{US} and TS_c^{R} are our measures of county-level exposure to the US and Retaliatory Tariff Shocks, respectively. $AgSubs_c$ is the estimated county-level agricultural subsidy per worker received under the 2018 Market Facilitation Program; we also include the interaction between $AgSubs_c$ and TS_c^{R} to examine whether the subsidies directly offset any of the Retaliatory Tariff Shock. $HInsur_c$ is a two-dimensional vector that comprises the average health insurance coverage share in 2013-2017, and the change in this local coverage share since the passage of the ACA (relative to 2008-2012).

To capture pre-trends in voting patterns, the vector R_c comprises the lagged change in the Republican House vote share between 2014-2016 ($\Delta RVoteSh_c^{16,14}$) and between 2012-2014 ($\Delta RVoteSh_c^{14,12}$). $RVoteSh_c^{P16}$ is the Republican vote share in the 2016 Presidential Election.[10] X_c is a vector of county-level initial characteristics covering demographics, employment shares by sector, and economic conditions – and their pre-trends – listed in Section 2.5. X_c also includes: (i) a set of four dummy variables that equal 1 if the county was uncontested by one of the major parties in either 2016 or 2018, but contested in the other year (to capture what would otherwise show up as a large swing in vote share); and (ii) a dummy variable for counties that are split across multiple CDs.[11]

Our model includes state fixed effects (D_s), which absorb any voting pattern differences arising from state ballot initiatives, Senate or Gubernatorial races. Equation (3) thus estimates the relationship between the 2018 trade shock and voting outcomes using within-state, cross-county variation. Throughout, we weight counties by population to avoid systematically over-representing rural voters. We also cluster standard errors two-ways by state and by commuting zone to allow for correlated shocks in the ϵ_c residuals, which could reflect unobserved political or economic forces along these geographic dimensions. Our analysis excludes counties where the same party won uncontested in both 2016 and 2018. We also report results excluding counties in Pennsylvania, which saw significant redistricting leading up to 2018; the estimates (available on request) are similar when these counties are included.

A second set of regressions explores whether the tariff shocks and agricultural subsidies exhibited heterogeneous effects on voting outcomes, depending on the competitiveness of the electoral landscape

[10] We obtain similar results if we were to replace $RVoteSh_c^{P16}$ with the set of competitiveness bin dummies, i.e., the $\mathbf{1}(c \in B^b)$'s, as in (4).

[11] Our results are unaffected if we drop these additional dummy variables.

in each county. For this, we estimate a flexible triple-interaction specification:

$$\begin{aligned}\Delta RVoteSh_c^{18,16} \quad = \quad & \sum_{b=1}^{6} \beta_1^b \mathbf{1}(c \in B^b) \times TS_c^{US} + \sum_{b=1}^{6} \beta_2^b \mathbf{1}(c \in B^b) \times TS_c^{R} \\ & + \sum_{b=1}^{6} \alpha_1^b \mathbf{1}(c \in B^b) \times AgSubs_c \times TS_c^R + \sum_{b=1}^{6} \alpha_2^b \mathbf{1}(c \in B^b) \times AgSubs_c \\ & + \delta HInsur_c + \eta R_c + \sum_{b=2}^{6} \gamma^b \mathbf{1}(c \in B^b) + \Gamma X_c + D_s + \epsilon_c. \qquad (4)\end{aligned}$$

Here, $\mathbf{1}(c \in B^b)$ is a dummy variable that equals 1 when county c belongs to "competitiveness bin" B^b, where $b = 1, 2, \ldots, 6$ refer respectively to the set of counties where the 2016 Trump vote share was 0-30%, 30-40%, 40-50%, 50-60%, 60-70%, and 70-100%.[12] We view the 40-50% and 50-60% bins as the most politically competitive, since these are counties where Trump either narrowly lost or won the 2016 popular vote.

4 Results

4.1 Baseline Findings

Table 2 presents the main results. Panel A reports the ordinary-least-squares estimates of (3), while Panel B contains results from (4). To limit table length, we report only the key coefficients of interest here; Table A.2 in the Appendix reports the full set of coefficients for the control variables and pre-trends. In Column 1, we exclude from the estimating equation all terms related to agricultural subsidies (both $AgSubs_c$ and its interactions) and to health insurance (the vector $HInsur_c$). Column 2 introduces $HInsur_c$ to the right-hand side, while Column 3 is the full specification as in (3) and (4).

Focus first on Panel A. Republican candidates lost vote share in the 2018 House election (relative to 2016) in counties where workers faced greater exposure to the Retaliatory Tariff Shock. The coefficient is stable across all three columns, ranging from -0.034 in Column 1 to -0.041 in Column 3. This last estimate implies that a one standard deviation increase in exposure to retaliatory tariffs (0.294, from Table 1) is associated with a $0.041 \times 0.294 \approx 1.2$ percentage point loss in vote share; in comparison, the mean cross-county drop in voter support for Republican House candidates was -6.4 percentage points. At the same time, we find no statistically significant relationship between exposure to the US Tariff Shock and $\Delta RVoteSh_c^{18,16}$.

The health care variables are also systematically related to the observed shifts in voting patterns.

[12]Equation (4) does not include a main effect term for TS_c^R, as this is already subsumed by the full set of interaction terms, $\mathbf{1}(c \in B^b) \times TS_c^R$, for $b = 1, 2, \ldots, 6$. For an analogous reason, we do not spell out the main effect terms for TS_c^{US} and $AgSubs_c$, and the double interaction term for $AgSubs_c \times TS_c^R$, on the right-hand side.

Table 2: Tariff Retaliation and Voting Patterns in the 2018 House Elections

Dep. variable: Δ **Republican House vote share (2018-2016)**	(1)		(2)		(3)	
Panel A: Average Effect of Tariff Shock						
US tariff shock	0.006	[0.010]	0.005	[0.010]	0.006	[0.010]
Retaliatory tariff shock	-0.034	[0.015]	-0.036	[0.016]	-0.041	[0.016]
Retaliatory tariff shock × Ag. subsidy					0.015	[0.007]
Ag. subsidy					0.004	[0.007]
Health insurance share (2013-17 avg.)			0.263	[0.092]	0.258	[0.093]
Δ Health insurance share (2013-17 minus 2008-12)			-0.248	[0.108]	-0.245	[0.107]
Lag Δ Rep. House vote share (2016 minus 2014)	-0.451	[0.090]	-0.449	[0.090]	-0.450	[0.090]
Lag Δ Rep. House vote share (2014 minus 2012)	-0.205	[0.042]	-0.201	[0.041]	-0.201	[0.041]
Republican Presidential vote share (2016)	-0.063	[0.040]	-0.067	[0.039]	-0.067	[0.039]
County initial controls and pre-trends	Y		Y		Y	
State FEs	Y		Y		Y	
Observations	3,011		3,011		3,011	
R^2	0.672		0.675		0.675	
Panel B: Heterogeneous Effects by Competitiveness Bins						
US tariff shock × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$)	0.112	[0.069]	0.103	[0.069]	0.105	[0.070]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)	-0.017	[0.068]	-0.022	[0.065]	-0.019	[0.066]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)	-0.013	[0.035]	-0.009	[0.035]	-0.004	[0.035]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)	0.033	[0.021]	0.032	[0.021]	0.031	[0.021]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)	-0.005	[0.009]	-0.007	[0.009]	-0.007	[0.009]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.7, 1]$)	-0.004	[0.006]	-0.005	[0.006]	-0.004	[0.006]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$)	-0.083	[0.059]	-0.089	[0.062]	-0.091	[0.064]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)	-0.046	[0.090]	-0.045	[0.089]	-0.054	[0.096]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)	-0.153	[0.050]	-0.166	[0.045]	-0.178	[0.050]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)	-0.021	[0.024]	-0.023	[0.023]	-0.022	[0.024]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)	0.001	[0.016]	0.001	[0.016]	-0.001	[0.016]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.7, 1]$)	-0.003	[0.008]	-0.004	[0.007]	-0.005	[0.007]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$)					0.261	[0.443]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)					0.194	[0.168]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)					0.473	[0.173]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)					-0.060	[0.039]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)					-0.011	[0.008]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.7, 1]$)					0.002	[0.005]
Health insurance share (2013-17 avg.)			0.303	[0.092]	0.303	[0.090]
Δ Health insurance share (2013-17 minus 2008-12)			-0.250	[0.107]	-0.252	[0.108]
Lag Δ Rep. House vote share (2016 minus 2014)	-0.448	[0.085]	-0.447	[0.085]	-0.445	[0.085]
Lag Δ Rep. House vote share (2014 minus 2012)	-0.199	[0.040]	-0.195	[0.040]	-0.193	[0.040]
Main effects: $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$),...	Y		Y		Y	
Double interactions: Ag. subsidy × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$),...	N		N		Y	
County initial controls and pre-trends	Y		Y		Y	
State FEs	Y		Y		Y	
Observations	3,011		3,011		3,011	
R^2	0.696		0.700		0.701	

Notes: All estimates are from least squares regressions, with observations weighted by total county population in 2016. The sample excludes counties in Pennsylvania (due to congressional redistricting), and counties where the same party won uncontested in both 2016 and 2018. All columns control for: county age, gender, and race shares in 2016 (from the US Census), as well as pre-trends between 2013-2016; county employment shares in agriculture, mining, and manufacturing respectively in 2016 (from the County Business Patterns), as well as pre-trends between 2013-2016; the county unemployment rate, log mean household income, and share with some college education in 2013-2017 (from the American Community Survey), as well as pre-trends between 2008-2012 and 2013-2017. All columns also include: (i) four indicator variables for counties contested by only one party in 2016 or 2018, but not both years; and (ii) an indicator variable for counties that are split across multiple congressional districts. We control in Panel B for the main effects of $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$),..., $\mathbf{1}$(Pres. vote $\in (0.7, 1]$), and in Column 3 for the double interaction terms in Ag. subsidy × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$),..., Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.7, 1]$), although the coefficients are not reported to save space. Standard errors are two-way clustered by state and commuting zone.

The coefficient on the initial (2013-2017 average) share of health insurance coverage is positive, suggesting that counties with greater coverage were more likely to support Republican candidates. Holding the level of coverage in 2013-2017 constant however, Republicans lost vote share in counties that saw larger increases in health insurance coverage following the passage of the ACA (relative to 2008-2012). This effect is economically meaningful: a one standard deviation greater expansion in health insurance coverage (0.031, from Table 1) is associated with a $0.245 \times 0.031 \approx 0.8$ percentage-point loss in vote share.

Agricultural subsidies played a more subtle role. In Column 3, although $AgSub_c$ exhibits no systematic relationship with voting patterns on its own, the positive coefficient (0.015) on the interaction term indicates the subsidy dampened Republicans' electoral losses from the retaliatory tariffs. In particular, the point estimates suggest that the MFP would have more than offset the Retaliatory Tariff Shock in the 124 counties that received subsidy amounts above $(0.041/0.015) \times \$1000 \approx \$2,733$ per worker. That said, these counties accounted for only 0.2% of the total US population in 2016.

The negative coefficients on the Republican vote share changes from the 2014-2016 and 2012-2014 election cycles suggest mean reversion: Republicans lost ground in counties where they had gained the most in the prior two House elections. Finally, as reported in Table A.2, several other county-level controls exhibit well-known relationships with voting outcomes: Republican candidates continued to fare better in counties with more old or white voters, and with lower rates of college education.

Panel B investigates whether the effects of the tariffs varied with the political competitiveness of the county. We find no statistically significant relationship between US tariff protection and vote share in any competitiveness bin. In contrast, the estimated effects of the Retaliatory Tariff Shock and agricultural subsidies are concentrated in counties where the Republican party narrowly lost the majority vote in the 2016 Presidential election.[13] The magnitude of the coefficients for this 40-50% bin are also larger than the average effects estimated earlier in Panel A: a one standard deviation increase in TS_c^R (0.18 among these counties, from Panel C of Table 1) is associated with a $0.178 \times 0.18 \approx 3.2$ percentage point loss in the Republican House vote share.[14]

Table 3 explores the sectoral dimension of the tariffs. Here, we decompose TS_c^R into the respective components due to tariffs on agricultural versus non-agricultural products. Columns 1 and 2 indicate that tariffs on agricultural products are driving the negative relationship between the Retaliatory Tariff Shock and Republican support, with no significant relationship detected for the non-agricultural component. Interestingly, we now find in Panel B a negative and statistically significant relationship between Republican support and retaliatory tariffs in both the 40-50% and 50-60% competitiveness bins. These patterns are broadly replicated in Column 3, where we further limit the agricultural and non-agricultural retaliatory shocks to that imposed by China; the results suggest that China's tariffs

[13] Figure A.1 in the Appendix illustrates that these pivotal counties are spread out throughout the US, albeit with fewer such counties present in the central plain states.

[14] In an analogous exercise, Table A.5 finds that the negative relationship between recent health insurance coverage gains and Republican support were concentrated in the 50-60% bin.

Table 3: Agricultural vs Non-Agricultural Tariff Shocks

Dep. variable: Δ **Republican House vote share (2018-2016)**	(1)		(2)		(3)	
Retaliatory tariff shock from CHN, CAN, MEX, EU:	All four		All four		CHN only	
Panel A: Average Effect of Tariff Shock						
US tariff shock	0.008	[0.012]	0.007	[0.012]	0.003	[0.010]
Retaliatory tariff shock, Ag.	-0.032	[0.016]	-0.039	[0.016]	-0.040	[0.017]
Retaliatory tariff shock, Ag. × Ag. subsidy			0.014	[0.008]	0.015	[0.008]
Retaliatory tariff shock, non-Ag.	-0.049	[0.034]	-0.052	[0.035]	-0.059	[0.039]
Retaliatory tariff shock, non-Ag. × Ag. subsidy			0.016	[0.030]	0.030	[0.042]
Ag. subsidy			0.004	[0.007]	0.004	[0.006]
Health insurance share (2013-17 avg.)	0.262	[0.092]	0.257	[0.093]	0.254	[0.093]
Δ Health insurance share (2013-17 minus 2008-12)	-0.250	[0.107]	-0.247	[0.106]	-0.249	[0.106]
Lag Δ Rep. House vote share (2016 minus 2014)	-0.449	[0.090]	-0.450	[0.090]	-0.450	[0.090]
Lag Δ Rep. House vote share (2014 minus 2012)	-0.201	[0.041]	-0.201	[0.041]	-0.201	[0.041]
Republican Presidential vote share (2016)	-0.067	[0.039]	-0.066	[0.039]	-0.067	[0.039]
County initial controls and pre-trends	Y		Y		Y	
State FEs	Y		Y		Y	
Observations	3,011		3,011		3,011	
R^2	0.675		0.675		0.675	
Panel B: Heterogeneous Effects by Competitiveness Bins						
US tariff shock × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$)	0.175	[0.062]	0.179	[0.061]	0.166	[0.069]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)	-0.004	[0.071]	-0.001	[0.072]	0.001	[0.072]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)	0.031	[0.035]	0.034	[0.036]	0.017	[0.034]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)	-0.023	[0.030]	-0.022	[0.031]	0.002	[0.025]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)	-0.009	[0.012]	-0.009	[0.012]	-0.010	[0.009]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.7, 1]$)	-0.003	[0.007]	-0.003	[0.007]	-0.005	[0.006]
Retaliatory tariff shock, Ag. × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$)	-0.040	[0.047]	-0.045	[0.049]	-0.062	[0.055]
Retaliatory tariff shock, Ag. × $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)	0.049	[0.103]	0.048	[0.107]	0.015	[0.108]
Retaliatory tariff shock, Ag. × $\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)	-0.115	[0.035]	-0.127	[0.037]	-0.150	[0.037]
Retaliatory tariff shock, Ag. × $\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)	-0.038	[0.019]	-0.037	[0.019]	-0.036	[0.020]
Retaliatory tariff shock, Ag. × $\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)	0.001	[0.017]	-0.002	[0.020]	-0.003	[0.021]
Retaliatory tariff shock, Ag. × $\mathbf{1}$(Pres. vote $\in (0.7, 1]$)	-0.002	[0.008]	-0.005	[0.008]	-0.006	[0.008]
Retaliatory tariff shock, Ag. × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$)			1.820	[2.079]	1.972	[2.272]
Retaliatory tariff shock, Ag. × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)			0.021	[0.270]	0.043	[0.272]
Retaliatory tariff shock, Ag. × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)			0.404	[0.182]	0.440	[0.187]
Retaliatory tariff shock, Ag. × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)			-0.053	[0.033]	-0.066	[0.036]
Retaliatory tariff shock, Ag. × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)			-0.014	[0.013]	-0.013	[0.014]
Retaliatory tariff shock, Ag. × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.7, 1]$)			0.005	[0.005]	0.005	[0.006]
Health insurance share (2013-17 avg.)	0.292	[0.091]	0.293	[0.090]	0.299	[0.092]
Δ Health insurance share (2013-17 minus 2008-12)	-0.219	[0.103]	-0.218	[0.104]	-0.225	[0.104]
Lag Δ Rep. House vote share (2016 minus 2014)	-0.453	[0.085]	-0.452	[0.085]	-0.447	[0.085]
Lag Δ Rep. House vote share (2014 minus 2012)	-0.194	[0.039]	-0.192	[0.039]	-0.190	[0.038]
Main effects: $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$),...	Y		Y		Y	
Double interactions: Ag. subsidy × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$),...	N		Y		Y	
Double interactions: Retaliatory tariff shock, non-Ag. × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$),...	N		Y		Y	
Triple interactions: Retaliatory tariff shock, non-Ag. × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$),...	N		Y		Y	
County initial controls and pre-trends	Y		Y		Y	
State FEs	Y		Y		Y	
Observations	3,011		3,011		3,011	
R^2	0.704		0.706		0.707	

Notes: Column 1 follows the specification in Column 2 of Table 2, while Columns 2-3 follow that in Column 3 of Table 2. The retaliatory tariff shock examined in Columns 1-2 is that imposed by China, Canada, Mexico and the EU; Column 3 limits the retaliatory tariff shock to that imposed by China only. In Panel B, we control for the main effects of $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$),..., $\mathbf{1}$(Pres. vote $\in (0.7, 1]$) in all columns. Columns 2-3 further include the double interactions in the Ag. subsidy and the presidential vote competitiveness bins, the double interactions in the non-agricultural retaliatory tariff shock and the competitiveness bins, as well as the triple interactions in the non-agricultural retaliatory tariff shock, the Ag. subsidy, and the competitiveness bins; coefficients are not reported to save space. Standard errors are two-way clustered by state and commuting zone.

on US farm exports may have played a particularly strong role in eroding the Republican vote share in the 2018 election.

We conduct additional robustness checks, described in detail in the Appendix. First, we consider alternative treatments of the electoral competitiveness of counties that are split across multiple CDs, and which are therefore exposed to forces from more than one House race. Our key results are robust even among just the subset of counties that fall in only one CD. Our results also hold when using a weighted-average of the CD-wide Republican vote shares in the 2016 Presidential election to define competitiveness bins (Table A.3). Second, we examine whether tariff shocks at the broader commuting zone (CZ) level might spill over to influence voting patterns. Again, our key results are robust. Moreover, controlling for county-level exposure, we find that the tariff exposure of the rest of the CZ has no discernible relationship with voting (Table A.4).

4.2 Counterfactuals

While the implied effects of the trade war discussed above are informative, measuring outcomes in terms of changes in average vote shares overlooks how the specific geographic incidence of the trade shock may have affected actual election winners and losers. In this section, we translate our regression results into counterfactual aggregate election outcomes: how many more House seats Republicans would have won but for the estimated influence of the trade war and health care policy.

We consider three counterfactual scenarios, namely how Republicans would have fared: (i) absent the trade war writ large (i.e., removing the estimated effects of retaliatory tariffs *and* agricultural subsidies); (ii) absent the agricultural subsidies *only* (but including the estimated political consequence of retaliatory tariffs); and (iii) absent the political influence of recent health insurance coverage gains. Table 4 summarizes our findings, which are calculated based on the point estimates from the full specification in Panel B, Column 3 of Table 2. In scenario (i), for example, we obtain the counterfactual county-level vote shares by subtracting the $\sum_{b=1}^{6} \beta_2^b \mathbf{1}(c \in B^b) \times TS_c^R$ and $\sum_{b=1}^{6} \alpha_1^b \mathbf{1}(c \in B^b) \times AgSubs_c \times TS_c^R$ terms from the actual 2018 Republican vote share for county c.

The upper panel reports implications for the Republican vote share, aggregating over all House races to the national level.[15] The first column reports the actual data as a benchmark, followed by results under each of the three scenarios. In the data, Republican House candidates saw a 4.83 percentage point decline in vote share nationwide, compared to 2016.[16] Comparing this figure to our estimated counterfactuals across the first row, we find that the trade war (including remedial agricultural subsidies) can account for $(0.048 - 0.043) \times 100 = 0.5$ percentage points, or about one-tenth of the observed decline in Republicans' nationwide House vote share. In contrast, removing

[15]Throughout the counterfactuals, we hold constant the total number of votes cast in a county, while altering the Republican share of votes according to our regression estimates.

[16]Note that the average cross-county change of -6.4 percentage points reported in Table 1 is an unweighted mean across counties. Weighting the change in county-level vote shares by total county votes, the two figures coincide (by definition).

Table 4: Implied Effects of the Tariff War on 2018 Voting Outcomes

	Data	Counterfactuals		
		Remove retal. tariffs and Ag. subsidies	Remove Ag. subsidies only	Remove health insurance gains
	A: Implied shift in Republican vote share			
National change: All counties	-0.048	-0.043	-0.048	-0.039
By competitiveness bins:				
$\mathbf{1}$(Pres. vote $\in [0, 0.3]$)	-0.019	-0.016	-0.019	-0.007
$\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)	-0.043	-0.039	-0.043	-0.033
$\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)	-0.045	-0.034	-0.045	-0.035
$\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)	-0.065	-0.057	-0.065	-0.056
$\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)	-0.056	-0.054	-0.057	-0.048
$\mathbf{1}$(Pres. vote $\in (0.7, 1]$)	-0.066	-0.067	-0.065	-0.057
	B: Implied net gain of CDs for the Democratic party			
Actual swing:	Gain of 36			
Assumed county-by-CD weights:				
Uniform vote share within county	53	48	53	46
Non-uniform, based on 2016	24	16	25	15
Non-uniform, based on 2018	36	31	36	28

Notes: Implied effects are computed based on the coefficient estimates from the regression in Panel B, Column 3, Table 2. The four columns report effects respectively: from the data; under a scenario where both the retaliatory tariffs and agricultural subsidies are removed; where only the agricultural subsides are removed; and where the five-year average gains in health insurance coverage are removed. The top panel reports the implied change in the Republican vote share; the vote share changes at the county level are first computed, and then aggregated up to either the national level or by electoral competitiveness bins. The bottom panel reports the net gain in House seats for the Democratic party, namely the number of seats where the Republican two-party vote share was > 0.5 in 2016 but the predicted vote share dropped to < 0.5 in 2018, less the number of seats where the Republican two-party vote share was < 0.5 in 2016 but the predicted share was > 0.5 in 2018. The first row is computed on the assumption that the vote share received by the Republican party is uniform within each county across all constituent county-by-CD partitions. The remaining rows relax this uniformity assumption, using instead the reported share of Republican (respectively, Democratic) votes within a county accounted for by each county-by-CD to break up the Republican (respectively, Democratic) predicted vote at the county level, before aggregating to the CD level; the second row does this on the basis of the 2016 county-by-CD voting outcomes, while the third row uses the 2018 voting outcomes. The sample considered here excludes Pennsylvania due to redistricting; adding the net gain of 4 seats for the Democratic party in Pennsylvania would bring the actual total net gain to 40 seats.

only the agricultural subsidies would have had a negligible effect on Republican support. Although the subsidies are important for the largest recipient counties, these are also counties with such small populations that there is little influence on nationwide vote totals. In contrast, health insurance accounts for $(0.048 - 0.039) \times 100 = 0.9$ percentage points, or about one-fifth of the erosion of Republican vote share. Health care was thus independently important and, on average, about twice as influential as the trade war. Nevertheless, in the most competitive counties where Trump narrowly lost a majority in 2016 (the 40-50% bin), an analogous calculation finds the trade war and health insurance to have commensurate and larger influence than at the national level. Each force accounts for about one-quarter of Republicans' vote share losses in such counties.

The lower panel translates the vote share changes into implied House seats. This exercise requires making assumptions about how to apportion the implied change in county-level voting when counties are split across multiple CDs. Our first and simplest approach assumes that a county's Republican vote share is uniformly distributed across any CD with which it overlaps. Under this assumption, we divide the votes cast at the county level for each party in the 2018 House elections into each county-by-CD partition, in proportion to the total votes cast (summed over both parties) in each county-by-CD partition from the earlier 2016 House elections (from Election Atlas).[17] Aggregating to the CD level, we can then count the implied number of seats won by each party. That exercise, reported in Column 1, yields a net swing to the Democratic party of 53 seats, which exceeds the actual swing of 36 seats observed in our sample (excluding Pennsylvania). This difference in the predicted versus actual seat swing can be interpreted as the number of additional seats that Republicans may have lost, absent the strategic gerrymandering of CD boundaries.

A second approach allows each county-by-CD partition to differ in importance to each party. Here, we divide the votes cast at the county level for the Republican party (respectively, Democratic party) using weights that are proportional to the Republican (respectively, Democratic) votes in each county-by-CD partition. Basing these weights on the county-by-CD figures from the 2016 House election, we obtain an under-estimate – a net swing of 24 seats – towards the Democrats. In contrast, using weights based on the 2018 county-by-CD figures yields exactly the net swing of 36 seats. This makes intuitive sense, as the 2018 data incorporate information about shifts in the importance of each county-by-CD partition for each parties' county-level performance.

We compute the implied seat swing for the three hypothetical scenarios by converting the counterfactual county-level vote shares to CD-level race outcomes, under each approach. Focusing on the last row in Table 4, which adopts the more realistic (non-uniform) apportioning rule based on the 2018 party-specific county-by-CD weights, our regression results suggest that the trade war cost Republicans a net 36-31=5 House seats. Under scenario (ii), where the retaliatory tariffs are in place, but no agricultural subsidies were extended, we find that the subsidies had no estimated impact on the predicted number of House seats. The MFP thus appears to have had minimal bearing on race outcomes, likely due to the geographically-narrow impact of the subsidies. Under scenario (iii), we find that the removal of health insurance as a policy issue would have resulted in a net swing of 28 seats, accounting for 36-28=8 Republican seats lost. This larger estimated impact of health care policy on House seats is consistent with the broader geographic spread of health insurance coverage gains in preceding years across the US, which likely put more CDs 'in play' than the Retaliatory Tariff Shock. Finally, if we were to combine scenarios (i) and (iii), we would obtain a net swing of 15 seats lost; the two forces thus overlap to jointly push several marginal CDs over from the Republican to the Democratic win column. (Appendix Figure A.2 presents a CD-level visualization for these counterfactual estimates of how much the trade war and health care policy affected the Republican party in the 2018 House elections.)

[17] See the Appendix for a more formal description of the apportioning assumptions and computation of CD-level outcomes.

5 Conclusion

We find that greater local exposure to the economic consequences of the trade war was associated with a decline in support and a loss of seats for Republican candidates in the 2018 House elections. This negative association was driven largely by retaliatory tariffs on agricultural products, particularly in political swing counties where Trump narrowly lost the popular vote in 2016. At the same time, the 2018 agricultural subsidies offset some of the Republican loss in vote share, although this was likely immaterial to the swing in House seats due to the narrow set of recipient counties. Our results are robust to a host of alternative specifications and control variables, including proxies for the importance of health care as central policy issue during the 2018 election.

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A Appendix

A.1 Data Details

Tariff Rates: The information on the tariffs introduced by the Trump administration, and in response by the US' major trading partners, was collected by Bown (2019). These were compiled for product codes at the tariff-line level. For the tariff increases levied by the US, the data cover the following: (i) on washers and solar panels, under Section 201, implemented in February 2018; (ii) on steel and aluminum, under Section 232, implemented in March and June 2018; (iii) on China, under Section 301, three separate lists of increases implemented in July, August and September 2018. (Note that for the tariffs on China, the increases implemented in July and August 2018 were the so-called '\$50 billion tariff list', i.e., covering \$50 billion of US imports from China; the subsequent increases in September 2018 covered an additional \$200 billion of US imports from China.) For the retaliatory tariffs, we include the tariff responses enacted by Canada, Mexico, China, and the EU to the above increases; these trading partners are the four largest sources of US imports, accounting for about two-thirds of the total value of US imports in 2017. (For a comprehensive timeline of US and retaliatory tariff actions, see Bown and Kolb (2019).)

County-level Tariff Shocks: We construct the county-level tariff shocks from the raw tariff rate increases as follows. Let $\Delta(\tau_p^{o,US})$ denote the tariff rate change imposed by the US on imports from country o in HS product p; as a convention, the first superscript denotes the origin country of the trade flows while the second superscript denotes the destination country. Thus, $\Delta(\tau_p^{US,d})$ refers instead to the retaliatory tariff rate increase on US exports to country d in product p. Next, define $X_p^{o,d}$ to be the value of product-p trade flows from country o to country d in an initial pre-tariff year. In practice, we use 2017 trade data from the World Bank WITS database for all countries, except for Canada where the most recent available year is 2016. The impact of the product-p tariff increase in dollar terms is then captured as: $TS_p^{o,d} = X_p^{o,d}\Delta(\tau_p^{o,d})$, this being the magnitude of tariff revenues that would be raised holding trade flows constant at their initial level.

We map these product-level shocks to US counties in two steps. As the US county-level data on industry composition is in NAICS codes, we first map the HS 6-digit tariff shocks to NAICS 3-digit industries, using HS-to-NAICS concordance weights constructed from the US customs data in Feenstra, Romalis, and Schott (2002). We use the US import data from 2002-2006 to construct weights for the US tariffs, while we use the US export data from those years to construct weights for the retaliatory tariffs. (We use 2002-2006 as these are the latest years available in Feenstra, Romalis, and Schott (2002); we exclude years prior to 2002 as there was an update to the HS codings in 2002.) The tariff shock from the US tariffs levied against country o that is experienced by NAICS industry i is then computed as: $TS_i^{o,US} = \sum_p \omega_{p,i}^{USimp} TS_p^{o,US}$, where $\omega_{p,i}^{USimp}$ is the share of US imports (summed over 2002-2006) in product p that is simultaneously classified in the US customs data as being in NAICS industry i. Similarly, the retaliatory tariff shock levied by country d that falls on NAICS industry i is computed as: $TS_i^{US,d} = \sum_p \omega_{p,i}^{USexp} TS_p^{US,d}$, where $\omega_{p,i}^{USexp}$ is the share of US exports (summed over 2002-2006) in product p that is classified in the US customs data as being in NAICS industry i.

The second step is to map the above industry-level tariff shocks experienced at the national level to the county level. For this, we use data on employment patterns by county and NAICS industry from the 2016 County Business Patterns (CBP). Let $L_{i,c}$ denote total employment reported in industry i and county c (from the CBP); L_i denote the total employment in that industry in the US (from the CBP); and $\bar{L}_c$ denote the total workforce size in that county (proxied for by the population aged 15-64, from the US Census county-level estimates for 2016). The county-level tariff shocks arising from the US tariff action and from the retaliatory tariffs are respectively constructed as:

$$TS_c^{US} = \sum_o \sum_i \frac{L_{i,c}}{L_i} \frac{TS_i^{o,US}}{\bar{L}_c}, \text{ and} \tag{A.1}$$

$$TS_c^{R} = \sum_d \sum_i \frac{L_{i,c}}{L_i} \frac{TS_i^{US,d}}{\bar{L}_c}. \tag{A.2}$$

Intuitively, this apportions the tariff shock at the NAICS industry level to each county, according to the county's share of US employment in NAICS industry i, and then sums the tariff shock across all industries i and US trade partner countries (respectively, o and d) being considered. We further divide by $\bar{L}_c$ to arrive at a per-worker effect for county c.

Note that the tariff shock measures as constructed are additive across industries i and partner countries (o or d). For the purposes of Table 3, the agricultural sector tariff shocks are thus obtained by restricting the summations in (A.1) and (A.2) to NAICS industries i that start with the digit 1; the non-agricultural tariff shocks are the corresponding sums taken over all other industries. Likewise, the agricultural sector tariff shock arising from retaliation from China is obtained by limiting the summation in (A.2) to $d = CHN$ and NAICS industries i that start with the digit 1.

In practice, the CBP does not report employment data for NAICS 111 ("Crop production), NAICS 112 ("Animal production and aquaculture"), and NAICS 113 ("Forestry and logging"), even though trade in these industries was affected by the tariff increases. Instead, employment in "Support Activities" for these respective industries is reported under NAICS 1151, 1152, and 1153. As agricultural employment in these support activities would be impacted by the tariff action, we associate the labor employed in NAICS 1151 to NAICS 111, in NAICS 1152 to NAICS 112, and in NAICS 1153 to NAICS 113, when we construct the county-level tariff shock measures in (A.1) and (A.2). For confidentiality reasons, the county-level employment observations from the CBP are routinely infused with a small amount of white noise. We use the reported figures with noise as given, since these are in principle mean-unbiased observations. For a number of entries, the CBP suppresses the actual figures and reports instead an employment size "class flag", i.e., a letter code indicating the range within which the actual employment lies. If the employment of a NAICS 3-digit industry is suppressed in this manner, we replace it with the total employment at the corresponding NAICS 2-digit level less employment in all other 3-digit industries with the same leading two digits. If there are multiple 3-digit industries with suppressed employment flags under a given NAICS 2-digit heading, we first compute the total employment that can be attributed to these undisclosed 3-digit industries, and then reapportion this total employment in proportion to the midpoint of the "class flag" bin for the undisclosed 3-digit industries. If the employment at the NAICS 2-digit level is itself suppressed, we assign to it the midpoint of the "class flag" bin; although this last step can result in a negative employment estimate for some 3-digit industries, this happens very rarely in practice, and we replace any such observations with a zero.

Market Facilitation Program (MFP) Agricultural Subsidies: We estimate the total subsidies received by each county under the 2018 MFP, by combining information on: (i) the announced subsidy rates by commodity, and (ii) the initial output or inventory of each county by commodity. On (i), the subsidy rates are taken from the Congressional Research Service report on "Farm Policy: USDA's 2018 Trade Aid Package" (19 June 2019 update); see in particular Table 2 of the report. The set of commodities we consider and their associated subsidy rates are: Soybeans ($1.65 per bushel), Hogs ($8.00 per head of inventory), Cotton ($0.06 per pound), Sorghum ($0.86 per bushel), Milk ($0.12 per hundred pounds), Wheat ($0.14 per bushel), and Corn ($0.01 per bushel). On (ii), we use annual county level crop output data from 2017, as downloaded from the US Department of Agriculture's National Agricultural Statistics Service. The two exceptions are: Hogs, where we use annual inventory data from 2017, and Milk, where we use 2012 output data as that is the most recent available year. This covers all agricultural commodities included in the MFP, except the two smallest commodities by total output – Fresh sweet cherries and Shelled almonds – for which county-level output data are not available. The MFP subsidy per worker is calculated by summing across the estimated total subsidy disbursed across commodities to each county, and then dividing by the county population between ages 15-64, $\bar{L}_c$ (from the US Census, 2016 population estimates).

We have cross-checked the validity of our MFP subsidy estimates against information on actual disbursements from the Environmental Working Group's (EWG) Farm Subsidy Database. The EWG has been obtaining information on MFP subsidy disbursements from the USDA through a Freedom of Information Act request, and has made publicly available a list of the largest beneficiaries from the 2018 MFP subsidies. Using the "Top Recipients" file as of October 2018, and aggregating the available data up to the commodity by state level, we find a positive correlation of 0.79 between the EWG data and the MFP subsidy estimates we have computed.

Election Data: From David Leip's Atlas of U.S. Presidential Elections, for the 2012, 2014, 2016, and 2018 House elections, as well as the 2016 Presidential election. We use the data on voting results at the county level, as well as at the county-by-CD level. The raw data can be purchased at: https://uselectionatlas.org.

Employment shares: From the 2016 and 2013 County Business Patterns. The data by NAICS 3-digit industries were cleaned, with employment estimates computed for the suppressed data cells using the procedure described above in the discussion of the construction of the tariff shock measures. The agriculture, mining, and manufacturing sectors are defined respectively as the NAICS industries with leading digit 1, with leading digits 21, and with leading digit 3. In the regressions, the employment shares from 2016 are used as initial controls, while the corresponding changes in shares in 2016 relative to 2013 are used as pre-trend controls.

Demographics: From the US Census Bureau, 2016 and 2013 estimates of county population by characteristics. We use the population shares by age group (25-34, 35-44, 45-54, 55-64, 65 and over), by gender (female), and by race (black, white non-Hispanic, Hispanic). In the regressions, the population shares from 2016 are used as initial controls, while the corresponding changes in shares in 2016 relative to 2013 are used as pre-trend controls.

Unemployment rate, Mean household income, Education, Health insurance coverage: From the American Community Survey, five-year averages for 2013-2017 and for 2008-2012. The education variable used is the share with some college education. The health insurance variable used is the share of the civilian noninstitutionalized population with health insurance. In the regressions, the five-year averages for 2013-2017 are used as initial controls, while the corresponding changes in five-year averages in 2013-2017 relative to 2008-2012 are used as pre-trend controls.

B Supplementary Figures

Figure A.1 below identifies the set of swing counties, on the basis of the Republican vote share in the 2016 Presidential election. Counties where the Trump vote share was: (i) between 40-50%; and (ii) between 50-60%, are highlighted.

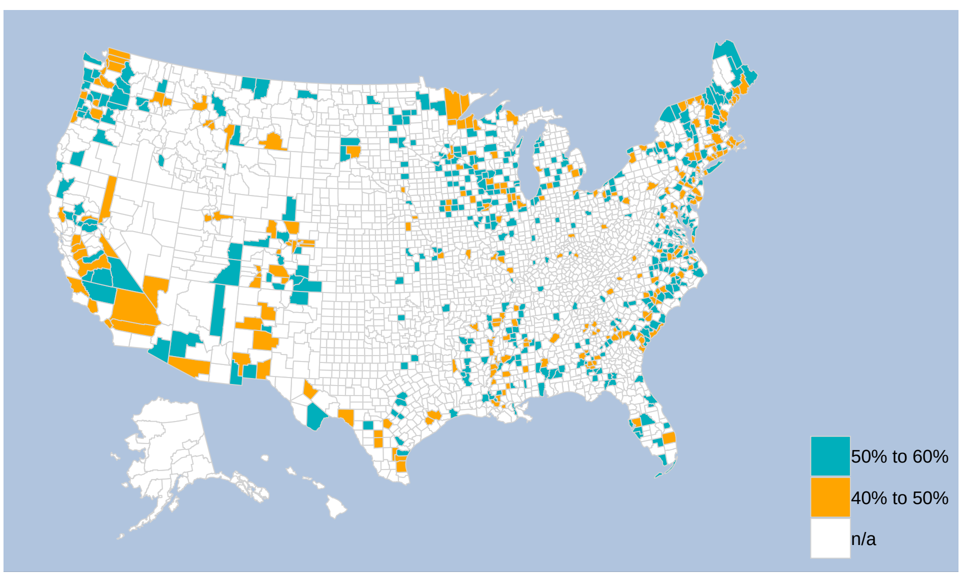

Figure A.1: Swing Counties
(2016 Republican Presidential Vote Share $\in [.4, .6]$)

Figure A.2 below is a Congressional District map that illustrates the predicted decrease in Republican House vote share that can be accounted for by the trade war (Panel A) and by health care policy (Panel B). These are computed from predicted county-level vote share changes, using the 'non-uniform' party-specific county-by-CD weights from 2018 (described in Section 4.2) to apportion the votes for counties that are split across multiple CDs. Panel A is based on the counterfactual where the effects related to both the retaliatory tariffs and agricultural subsidies are removed; this is scenario (i) from Section 4.2. Panel B is based on the counterfactual where the effects related to gains in health insurance coverage are removed; this is scenario (iii) from Section 4.2. The map excludes Pennsylvania, where the redistricting of CD boundaries precludes making predictions about how county-level vote shares would aggregate to the CD level, and Hawaii, where both CDs remained firmly in the Democratic column.

A: Trade War B: Health Insurance

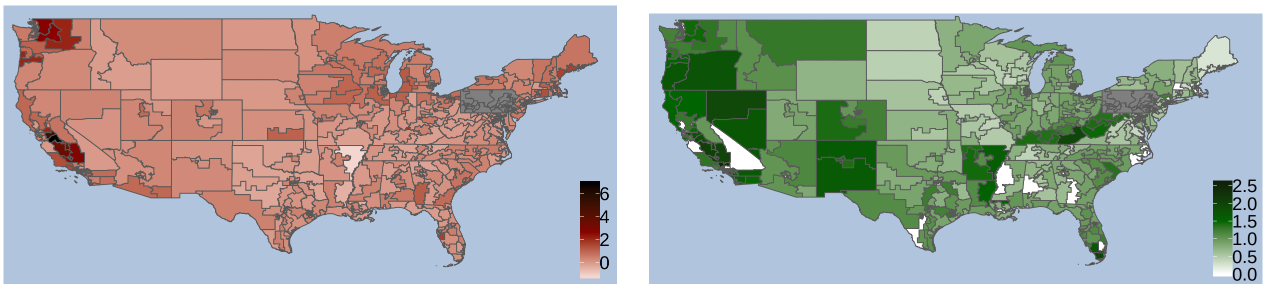

Figure A.2: Estimated Decline in 2018 House Republican Vote Share associated with the Trade War (Left) and Health Care Policy (Right)

C Further Details of Analysis

Section 4.1 (Robustness): We elaborate on the two sets of robustness checks that are briefly described at the end of Section 4.1. (Note that the appendix tables below report specifications that are based on those in Columns 2 and 3 of Table 2 in the main paper.)

In Table A.3, we examine alternative treatments to capture the inherent electoral competitiveness of a county. The underlying concern is that the county-level Republican vote share in the 2016 Presidential election may not adequately reflect the electoral competitiveness of a county that is split across multiple CDs, if there are forces specific to Congressional races that may have influenced voting patterns in the 2016 presidential race. Columns 1 and 2 adopt a blunt approach to address this issue, namely dropping from the sample all counties that overlap with multiple CDs; this nevertheless leaves 2,633 counties in the sample. We continue to obtain a negative effect of the Retaliatory Tariff Shock in those counties where the Trump vote share in 2016 was between 40-50%, with the coefficients remaining significant at the 10% level. Interestingly, we now obtain a positive and significant effect of the US Tariff Shock in the 50-60% "competitiveness bin", although this finding is likely driven by the composition of counties that remain in the sample. In Columns 3 and 4, we instead consider an alternative measure of electoral competitiveness that takes into account CD-wide conditions. Specifically, for each county, we calculate the weighted average of the CD-wide Republican vote share in the 2016 Presidential election, where the weights used are proportional to the total number of votes cast for the two major parties' candidates in the 2016 House election in each county-by-CD partition. (To be clear, the CD-wide vote share includes all votes cast in the CD, including the parts of the CD that are outside the county in question.) We then re-group the counties into the six competitiveness bins on the basis of this weighted-average measure. The regressions here continue to point to the effect of the Retaliatory Tariff Shock being concentrated in 'close' counties, with a negative and significant effect estimated in the 40-50% competitiveness bin, and now even in the 30-40% competitiveness bin.

Table A.4 explores the potential for spillover effects of trade shocks experienced in other parts of a county's commuting zone (CZ) to influence voting in the county. We construct the "Rest-of-CZ tariff shock" measure by aggregating over the US (respectively, Retaliatory) Tariff Shocks in the CZ, but outside the county in question. Specifically, we sum the $\frac{L_{i,c}}{L_i} TS_i^{o,d}$ terms in equations (A.1) and (A.2) across all counties within the CZ, except the county c in question; we then divide by the total working age population (between ages 15-64) located in the CZ, but outside the county c. (The mapping of counties to commuting zones is from: https://www.ddorn.net/data/cw_cty_czone.zip.) Columns 1 and 2 of this table show that accounting for the county-level exposure to the tariff shocks, the exposure of the rest of the CZ has no discernible relationship with voting outcomes, while the county-level estimates remain robust. In Columns 3 and 4, we examine an alternative "Full trade value" construction of the tariff shock measures. Specifically, we replace the product-level tariff shock with $TS_p^{o,d} = X_p^{o,d}$ in the construction of the trade shocks; this is in contrast to the baseline, where $TS_p^{o,d}$ was instead obtained by multiplying the initial value of trade by the tariff rate increase (i.e., $TS_p^{o,d} = X_p^{o,d} \Delta(\tau_p^{o,d})$). Our key findings on the negative impact of the Retaliatory Tariff Shock on the Republican House vote share, and the mitigating effect of the agricultural subsidies, remains unaffected under this alternative construction.

Section 4.2 (Counterfactuals): In this part of the Appendix, we document formally how the counterfactual implications of the regression model in (4) for county-level vote shares and CD-level race outcomes are computed.

Let $RVote_c^{18}$ and $DVote_c^{18}$ denote the number of votes cast for Republican and Democratic candidates respectively in county c in the 2018 House elections, as reported in the Election Atlas. Let $TVote_c^{18} \equiv RVote_c^{18} + DVote_c^{18}$ be the total number of votes cast in county c for Republican and Democratic candidates. In turn, define $RVoteSh_c^{18} \equiv RVote_c^{18} / TVote_c^{18}$ to be the 'two party vote share' received by Republican House candidates in county c, as computed directly from the Election Atlas data.

In what follows, we will use 'hats' ($\widehat{x}$) to denote predicted or counterfactual values of a variable x. Section 4.2 considers three hypothetical scenarios (i)-(iii). The counterfactual 2018 Republican House vote share, $\widehat{RVoteSh_c}^{18}$, is computed by subtracting from $RVoteSh_c^{18}$ the terms on the right-hand side of (4) that capture the forces of interest each scenario. Specifically:

- under scenario (i), where the effects of both the retaliatory tariffs and agricultural subsidies are removed, we compute the counterfactual Republican vote share as: $\widehat{RVoteSh}_c^{18} = RVoteSh_c^{18} - \sum_{b=1}^{6} \beta_2^b \mathbf{1}(c \in B^b) \times TS_c^R - \sum_{b=1}^{6} \alpha_1^b \mathbf{1}(c \in B^b) \times AgSubs_c \times TS_c^R$;

- under scenario (ii), where only the effect of the retaliatory tariffs is removed, we instead have: $\widehat{RVoteSh}_c^{18} = RVoteSh_c^{18} - \sum_{b=1}^{6} \beta_2^b \mathbf{1}(c \in B^b) \times TS_c^R$; and

- under scenario (iii), we compute $\widehat{RVoteSh}_c^{18}$ as $RVoteSh_c^{18}$ minus the effect of recent health insurance coverage gains (i.e., the increase in the county-c health insurance coverage share between 2008-2012 to 2013-2017 times its estimated regression coefficient).

Note that we use the point estimates from the full specification in Panel B of Table 2, Column 3, to calculate the above counterfactual vote shares.

We next convert these county-level implications to nation-wide vote share changes. For each scenario (i)-(iii), we compute the counterfactual number of votes received by Republican (respectively, Democratic) candidates in county c in 2018 as:

$$\begin{aligned} \widehat{RVote}_c^{18} &= \widehat{RVoteSh}_c^{18} \times TVote_c^{18}, \text{ and} \\ \widehat{DVote}_c^{18} &= (1 - \widehat{RVoteSh}_c^{18}) \times TVote_c^{18}; \end{aligned}$$

note that this calculation is made holding constant the total number of votes cast for the major party candidates ($TVote_c^{18}$) at the counts observed in the Election Atlas. Aggregating across the House races in all counties in our sample, we then obtain the counterfactual nation-wide Republican vote share as: $\sum_c \widehat{RVote}_c^{18} / (\sum_c \widehat{RVote}_c^{18} + \sum_c \widehat{DVote}_c^{18})$. We subtract from this the Republican House vote share in 2016 aggregated over the counties in our sample (computed directly from the Election Atlas data), to arrive at the Republican vote share change under each of the three counterfactual scenarios. These are the results reported in the upper panel of Table 4.

We further infer the implications for the number of House seats won by each party under each of the three scenarios. Let H_c denote the set of CDs which overlap with county c. For any given set of counterfactual vote counts, these now need to be apportioned for each county c to the CDs $h \in H_c$ which overlap with the county. Let $\omega_{c,h}^R \in [0,1]$ denote the weight used to apportion the Republican votes cast in county c, $\widehat{RVote}_c^{18}$, to each of the CDs $h \in H_c$, where: $\sum_{h \in H_c} \omega_{c,h}^R = 1$. Let $\omega_{c,h}^D \in [0,1]$ denote the analogous weight for apportioning $\widehat{DVote}_c^{18}$, with $\sum_{h \in H_c} \omega_{c,h}^D = 1$.

Our baseline 'uniform vote share' assumption sets: $\omega_{c,h}^R = \omega_{c,h}^D = (RVote_{c,h}^{16} + DVote_{c,h}^{16})/(RVote_c^{16} + DVote_c^{16})$. Here, $RVote_{c,h}^{16}$ (respectively, $DVote_{c,h}^{16}$) is the number of Republican (respectively, Democratic) votes in the 2016 House election recorded in the county-by-CD partition where CD h overlaps with county c, as reported in the Election Atlas. At the same time, $RVote_c^{16}$ (respectively, $DVote_c^{16}$) is the number of Republican (respectively, Democratic) votes cast in the 2016 House election in all of county c. Intuitively, these weights assume that Republican (respectively, Democratic) voter support is distributed uniformly across the CDs within a county, so that the Republican (respectively, Democratic) vote share is identical within each county-by-CD partition; the $\omega_{c,h}^R$ and $\omega_{c,h}^D$ weights are thus identical for both parties and proportional to the total number of votes cast (summed over the two parties) in the county-by-CD partition.

Under the 'non-uniform vote share' assumption, we instead allow for each county-by-CD partition to differ in importance to each party. Specifically, we set: $\omega^R_{c,h} = RVote^y_{c,h}/RVote^y_c$ and $\omega^D_{c,h} = DVote^y_{c,h}/DVote^y_c$, where $y = 16$ or 18 depending respectively on whether we use 2016 or 2018 Election Atlas data to construct these weights. $\omega^R_{c,h}$ and $\omega^D_{c,h}$ would therefore split up the counterfactual county-level vote counts, $\widehat{RVote}_c^{18}$ and $\widehat{DVote}_c^{18}$, according to the share of Republican (respectively, Democratic) votes cast within each county-by-CD partition in either the 2016 or 2018 House elections.

We can now compute the counterfactual vote counts for each party at the CD level as follows. Let C_h denote the set of counties c that overlap with CD h. The counterfactual vote counts for CD h in the 2018 House elections are then given by:

$$\begin{aligned}
\widehat{RVote}_h^{18} &= \sum_{c \in C_h} \omega^R_{c,h} \widehat{RVote}_c^{18}, \text{ and} \\
\widehat{DVote}_h^{18} &= \sum_{c \in C_h} \omega^D_{c,h} \widehat{DVote}_c^{18}.
\end{aligned}$$

This calculation can be performed for each of scenarios (i)-(iii), under each of the apportionment assumptions in turn. We then count up the number of House seats h for which: $\widehat{RVote}_h^{18}/(\widehat{RVote}_h^{18} + \widehat{DVote}_h^{18}) < 1/2$ and $RVote^{16}_h/(RVote^{16}_h + DVote^{16}_h) > 1/2$; we interpret these as seats that would have swung from the Republican to the Democratic win column from 2016 to 2018. Likewise, we count the number of House seats h for which: $\widehat{RVote}_h^{18}/(\widehat{RVote}_h^{18} + \widehat{DVote}_h^{18}) > 1/2$ and $RVote^{16}_h/(RVote^{16}_h + DVote^{16}_h) < 1/2$; these are seats that would have swung in the opposite direction, from the Democratic to the Republican party. We then take the difference between these two counts to infer the net swing in seats. The results for each of scenarios (i)-(iii), under each apportionment rule, are reported in the lower panel of Table 4.

D Supplementary Tables

Table A.1: Summary Statistics: Control Variables

	Mean	Std. Dev.	10th pct.	50th pct.	90th pct.
Employment shares by sector					
Employment share, Agriculture (2016)	0.035	0.079	0.000	0.007	0.101
Employment share, Mining (2016)	0.068	0.152	0.000	0.007	0.221
Employment share, Manufacturing (2016)	0.557	0.262	0.143	0.606	0.864
Δ Employment share, Agriculture (2016 minus 2013)	-0.004	0.061	-0.029	0.000	0.019
Δ Employment share, Mining (2016 minus 2013)	-0.017	0.084	-0.076	-0.000	0.013
Δ Employment share, Manufacturing (2016 minus 2013)	0.006	0.128	-0.091	-0.002	0.108
Demographics					
Population share, Age 25-34 (2016)	0.118	0.021	0.095	0.115	0.145
Population share, Age 35-44 (2016)	0.114	0.014	0.098	0.115	0.131
Population share, Age 45-54 (2016)	0.130	0.014	0.112	0.130	0.146
Population share, Age 55-64 (2016)	0.142	0.021	0.116	0.142	0.167
Population share, Age 65 and over (2016)	0.184	0.045	0.131	0.181	0.243
Population share, Female (2016)	0.499	0.022	0.479	0.503	0.517
Population share, Black (2016)	0.093	0.145	0.005	0.024	0.305
Population share, White non-Hispanic (2016)	0.769	0.198	0.464	0.842	0.954
Population share, Hispanic (2016)	0.094	0.138	0.015	0.041	0.241
Δ Population share, Age 25-34 (2016 minus 2013)	0.002	0.005	-0.004	0.002	0.007
Δ Population share, Age 35-44 (2016 minus 2013)	-0.002	0.005	-0.008	-0.002	0.004
Δ Population share, Age 45-54 (2016 minus 2013)	-0.009	0.006	-0.017	-0.009	-0.003
Δ Population share, Age 55-64 (2016 minus 2013)	0.004	0.005	-0.002	0.004	0.009
Δ Population share, Age 65 and over (2016 minus 2013)	0.013	0.007	0.005	0.012	0.021
Δ Population share, Female (2016 minus 2013)	-0.000	0.004	-0.004	-0.000	0.003
Δ Population share, Black (2016 minus 2013)	0.001	0.004	-0.002	0.001	0.005
Δ Population share, White non-Hispanic (2016 minus 2013)	-0.009	0.007	-0.018	-0.007	-0.002
Δ Population share, Hispanic (2016 minus 2013)	0.005	0.006	0.001	0.003	0.012
Economic conditions					
Unemployment rate (2013-17 avg.)	6.335	3.001	3.000	6.000	9.800
Log mean household income (2013-17 avg.)	11.058	0.223	10.801	11.040	11.329
Share with some college (2013-17 avg.)	0.517	0.107	0.381	0.516	0.653
Δ Unemployment rate (2013-17 minus 2008-12)	-2.288	2.686	-5.400	-2.200	0.700
Δ Log mean household income (2013-17 minus 2008-12)	0.103	0.079	0.017	0.100	0.194
Δ Share with some college (2013-17 minus 2008-12)	0.026	0.031	-0.007	0.026	0.061

Notes: Summary statistics across $N = 3,108$ counties, excluding Alaska. Total county population data are from the US Census (resident population, 2016 and 2013 estimates). The sectoral employment shares are from the County Business Patterns dataset (2016 and 2013 respectively). The unemployment rate, log mean household income, and share with some college education are from the American Community Survey (five-year average series, 2013-17 and 2008-12 respectively).

Table A.2: Tariff Retaliation and Voting Patterns in the 2018 House Elections (Full Table)

Dep. variable: Δ **Republican House vote share (2018-2016)**	(1)		(2)		(3)	
Panel A: Average Effect of Tariff Shock						
US tariff shock	0.006	[0.010]	0.005	[0.010]	0.006	[0.010]
Retaliatory tariff shock	-0.034	[0.015]	-0.036	[0.016]	-0.041	[0.016]
Retaliatory tariff shock × Ag. subsidy					0.015	[0.007]
Ag. subsidy					0.004	[0.007]
Health insurance share (2013-17 avg.)			0.263	[0.092]	0.258	[0.093]
Δ Health insurance share (2013-17 minus 2008-12)			-0.248	[0.108]	-0.245	[0.107]
Lag Δ Rep. House vote share (2016 minus 2014)	-0.451	[0.090]	-0.449	[0.090]	-0.450	[0.090]
Lag Δ Rep. House vote share (2014 minus 2012)	-0.205	[0.042]	-0.201	[0.041]	-0.201	[0.041]
Republican Presidential vote share (2016)	-0.063	[0.040]	-0.067	[0.039]	-0.067	[0.039]
Employment share, Agriculture (2016)	0.012	[0.058]	0.019	[0.057]	0.018	[0.057]
Employment share, Mining (2016)	0.033	[0.028]	0.035	[0.029]	0.038	[0.028]
Employment share, Manufacturing (2016)	-0.005	[0.021]	-0.004	[0.021]	-0.003	[0.021]
Δ Employment share, Agriculture (2016 minus 2013)	-0.020	[0.045]	-0.025	[0.044]	-0.016	[0.044]
Δ Employment share, Mining (2016 minus 2013)	-0.007	[0.042]	-0.011	[0.043]	-0.011	[0.043]
Δ Employment share, Manufacturing (2016 minus 2013)	0.025	[0.029]	0.019	[0.030]	0.019	[0.030]
Population share, Age 25-34 (2016)	-0.184	[0.186]	-0.140	[0.176]	-0.125	[0.176]
Population share, Age 35-44 (2016)	0.816	[0.390]	0.797	[0.372]	0.767	[0.368]
Population share, Age 45-54 (2016)	-0.439	[0.422]	-0.627	[0.413]	-0.597	[0.414]
Population share, Age 55-64 (2016)	0.372	[0.418]	0.644	[0.412]	0.621	[0.414]
Population share, Age 65 and over (2016)	0.279	[0.128]	0.236	[0.120]	0.228	[0.119]
Population share, Female (2016)	-0.238	[0.189]	-0.201	[0.187]	-0.194	[0.185]
Population share, Black (2016)	-0.122	[0.094]	-0.156	[0.089]	-0.159	[0.089]
Population share, White non-Hispanic (2016)	-0.092	[0.100]	-0.137	[0.096]	-0.137	[0.096]
Population share, Hispanic (2016)	-0.057	[0.087]	-0.059	[0.077]	-0.059	[0.077]
Δ Population share, Age 25-34 (2016 minus 2013)	1.014	[0.934]	0.678	[0.888]	0.699	[0.871]
Δ Population share, Age 35-44 (2016 minus 2013)	0.320	[1.213]	0.036	[1.218]	0.086	[1.210]
Δ Population share, Age 45-54 (2016 minus 2013)	-0.268	[0.998]	0.236	[0.977]	0.282	[0.970]
Δ Population share, Age 55-64 (2016 minus 2013)	-0.729	[0.691]	-0.645	[0.702]	-0.703	[0.708]
Δ Population share, Age 65 and over (2016 minus 2013)	-0.732	[0.586]	-0.910	[0.576]	-0.787	[0.586]
Δ Population share, Female (2016 minus 2013)	0.015	[1.188]	0.099	[1.194]	0.110	[1.186]
Δ Population share, Black (2016 minus 2013)	1.589	[0.735]	1.814	[0.714]	1.824	[0.712]
Δ Population share, White non-Hispanic (2016 minus 2013)	1.404	[0.656]	1.727	[0.654]	1.722	[0.658]
Δ Population share, Hispanic (2016 minus 2013)	0.743	[0.636]	1.065	[0.656]	1.084	[0.652]
Unemployment rate (2013-17 avg.)	0.002	[0.002]	0.002	[0.002]	0.002	[0.002]
Log mean household income (2013-17 avg.)	0.025	[0.024]	0.024	[0.022]	0.026	[0.022]
Share with some college (2013-17 avg.)	-0.265	[0.052]	-0.308	[0.051]	-0.305	[0.052]
Δ Unemployment rate (2013-17 minus 2008-12)	0.001	[0.001]	0.001	[0.001]	0.001	[0.001]
Δ Log mean household income (2013-17 minus 2008-12)	0.053	[0.044]	0.050	[0.046]	0.049	[0.046]
Δ Share with some college (2013-17 minus 2008-12)	0.170	[0.135]	0.186	[0.144]	0.178	[0.146]
1(Uncontested by Dem. in 2016, Contested in 2018)	-0.142	[0.026]	-0.141	[0.026]	-0.141	[0.027]
1(Uncontested by Rep. in 2016, Contested in 2018)	0.136	[0.074]	0.130	[0.074]	0.130	[0.074]
1(Contested in 2016, Uncontested by Dem. in 2018)	0.292	[0.060]	0.293	[0.060]	0.293	[0.060]
1(Contested in 2016, Uncontested by Rep. in 2018)	-0.210	[0.027]	-0.212	[0.027]	-0.212	[0.028]
1(County split across multiple CDs)	-0.006	[0.008]	-0.006	[0.007]	-0.006	[0.007]
County initial controls and pre-trends	Y		Y		Y	
State FEs	Y		Y		Y	
Observations	3,011		3,011		3,011	
R^2	0.672		0.675		0.675	

(Cont...)

Table A.2: Tariff Retaliation and Voting Patterns in the 2018 House Elections (Full Table, cont.)

Dep. variable: Δ **Republican House vote share (2018-2016)**	(1)		(2)		(3)	
Panel B: Heterogeneous Effects by Competitiveness Bins						
US tariff shock × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$)	0.112	[0.069]	0.103	[0.069]	0.105	[0.070]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)	-0.017	[0.068]	-0.022	[0.065]	-0.019	[0.066]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)	-0.013	[0.035]	-0.009	[0.035]	-0.004	[0.035]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)	0.033	[0.021]	0.032	[0.021]	0.031	[0.021]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)	-0.005	[0.009]	-0.007	[0.009]	-0.007	[0.009]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.7, 1]$)	-0.004	[0.006]	-0.005	[0.006]	-0.004	[0.006]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$)	-0.083	[0.059]	-0.089	[0.062]	-0.091	[0.064]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)	-0.046	[0.090]	-0.045	[0.089]	-0.054	[0.096]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)	-0.153	[0.050]	-0.166	[0.045]	-0.178	[0.050]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)	-0.021	[0.024]	-0.023	[0.023]	-0.022	[0.024]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)	0.001	[0.016]	0.001	[0.016]	-0.001	[0.016]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.7, 1]$)	-0.003	[0.008]	-0.004	[0.007]	-0.005	[0.007]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$)					0.261	[0.443]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)					0.194	[0.168]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)					0.473	[0.173]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)					-0.060	[0.039]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)					-0.011	[0.008]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.7, 1]$)					0.002	[0.005]
Health insurance share (2013-17 avg.)			0.303	[0.092]	0.303	[0.090]
Δ Health insurance share (2013-17 minus 2008-12)			-0.250	[0.107]	-0.252	[0.108]
Lag Δ Rep. House vote share (2016 minus 2014)	-0.448	[0.085]	-0.447	[0.085]	-0.445	[0.085]
Lag Δ Rep. House vote share (2014 minus 2012)	-0.199	[0.040]	-0.195	[0.040]	-0.193	[0.040]
$\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)	-0.028	[0.018]	-0.029	[0.018]	-0.029	[0.018]
$\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)	-0.012	[0.017]	-0.016	[0.018]	-0.015	[0.019]
$\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)	-0.056	[0.013]	-0.062	[0.013]	-0.063	[0.013]
$\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)	-0.041	[0.014]	-0.048	[0.014]	-0.049	[0.015]
$\mathbf{1}$(Pres. vote $\in (0.7, 1]$)	-0.019	[0.016]	-0.027	[0.016]	-0.027	[0.016]
Ag. subsidy × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$)					-0.071	[0.144]
Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)					-0.043	[0.046]
Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)					-0.169	[0.057]
Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)					0.046	[0.022]
Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)					0.015	[0.008]
Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.7, 1]$)					0.001	[0.007]
Employment share, Agriculture (2016)	0.032	[0.055]	0.040	[0.054]	0.040	[0.054]
Employment share, Mining (2016)	0.011	[0.028]	0.014	[0.028]	0.016	[0.028]
Employment share, Manufacturing (2016)	-0.008	[0.020]	-0.006	[0.020]	-0.006	[0.020]
Δ Employment share, Agriculture (2016 minus 2013)	-0.027	[0.047]	-0.032	[0.046]	-0.029	[0.047]
Δ Employment share, Mining (2016 minus 2013)	0.003	[0.038]	-0.001	[0.038]	-0.002	[0.038]
Δ Employment share, Manufacturing (2016 minus 2013)	0.030	[0.024]	0.023	[0.024]	0.022	[0.024]

(Cont…)

Table A.2: Tariff Retaliation and Voting Patterns in the 2018 House Elections (Full Table, cont.)

Dep. variable: Δ **Republican House vote share (2018-2016)**	(1)		(2)		(3)	
Panel B (cont.)						
Population share, Age 25-34 (2016)	-0.217	[0.189]	-0.181	[0.186]	-0.176	[0.188]
Population share, Age 35-44 (2016)	0.618	[0.313]	0.597	[0.298]	0.573	[0.298]
Population share, Age 45-54 (2016)	-0.231	[0.394]	-0.448	[0.398]	-0.419	[0.392]
Population share, Age 55-64 (2016)	0.177	[0.406]	0.448	[0.406]	0.411	[0.404]
Population share, Age 65 and over (2016)	0.242	[0.110]	0.199	[0.105]	0.192	[0.104]
Population share, Female (2016)	-0.213	[0.176]	-0.178	[0.172]	-0.185	[0.170]
Population share, Black (2016)	-0.085	[0.093]	-0.125	[0.089]	-0.123	[0.089]
Population share, White non-Hispanic (2016)	-0.079	[0.103]	-0.125	[0.100]	-0.123	[0.100]
Population share, Hispanic (2016)	-0.049	[0.087]	-0.053	[0.077]	-0.052	[0.077]
Δ Population share, Age 25-34 (2016 minus 2013)	0.809	[0.767]	0.475	[0.759]	0.445	[0.742]
Δ Population share, Age 35-44 (2016 minus 2013)	0.613	[1.175]	0.305	[1.196]	0.268	[1.188]
Δ Population share, Age 45-54 (2016 minus 2013)	-0.669	[1.067]	-0.161	[1.055]	-0.160	[1.058]
Δ Population share, Age 55-64 (2016 minus 2013)	-0.380	[0.849]	-0.230	[0.816]	-0.247	[0.846]
Δ Population share, Age 65 and over (2016 minus 2013)	-0.271	[0.598]	-0.451	[0.589]	-0.361	[0.598]
Δ Population share, Female (2016 minus 2013)	0.345	[1.108]	0.440	[1.120]	0.347	[1.122]
Δ Population share, Black (2016 minus 2013)	2.399	[0.595]	2.634	[0.564]	2.650	[0.573]
Δ Population share, White non-Hispanic (2016 minus 2013)	1.753	[0.585]	2.081	[0.611]	2.079	[0.616]
Δ Population share, Hispanic (2016 minus 2013)	1.984	[0.763]	2.339	[0.765]	2.334	[0.767]
Unemployment rate (2013-17 avg.)	0.002	[0.002]	0.002	[0.002]	0.003	[0.002]
Log mean household income (2013-17 avg.)	0.010	[0.028]	0.011	[0.027]	0.011	[0.027]
Share with some college (2013-17 avg.)	-0.196	[0.051]	-0.251	[0.048]	-0.245	[0.048]
Δ Unemployment rate (2013-17 minus 2008-12)	0.001	[0.001]	0.000	[0.001]	-0.000	[0.001]
Δ Log mean household income (2013-17 minus 2008-12)	0.042	[0.052]	0.037	[0.052]	0.038	[0.052]
Δ Share with some college (2013-17 minus 2008-12)	0.123	[0.127]	0.144	[0.137]	0.138	[0.138]
1(Uncontested by Dem. in 2016, Contested in 2018)	-0.151	[0.022]	-0.150	[0.022]	-0.150	[0.022]
1(Uncontested by Rep. in 2016, Contested in 2018)	0.139	[0.086]	0.132	[0.086]	0.132	[0.086]
1(Contested in 2016, Uncontested by Dem. in 2018)	0.291	[0.057]	0.292	[0.057]	0.293	[0.056]
1(Contested in 2016, Uncontested by Rep. in 2018)	-0.204	[0.032]	-0.207	[0.032]	-0.203	[0.033]
1(County split across multiple CDs)	-0.005	[0.007]	-0.005	[0.007]	-0.006	[0.007]
County initial controls and pre-trends	Y		Y		Y	
State FEs	Y		Y		Y	
Observations	3,011		3,011		3,011	
R^2	0.696		0.700		0.701	

Notes: The above table reproduces the regressions from Table 2, with coefficients of all control variables reported in full. The dependent variable is the change between 2016 and 2018 in the county-level two-party Republican House vote share. All estimates are from least squares regressions, with observations weighted by total county population in 2016. The US tariff shock, retaliatory tariff shock, and Ag. subsidy variables are in units of $1,000 per worker. The sample excludes counties in Pennsylvania (which saw congressional redistricting between 2016 and 2018), and those counties in which the same party won uncontested in both 2016 and 2018. Standard errors are two-way clustered by state and commuting zone.

Table A.3: Robustness: Alternative Treatments of Electorally-"Close" Counties

Dep. variable:	Δ Republican House vote share (2018-2016)							
	(1) Drop split counties		(2) Drop split counties		(3) Bins: Wtd-avg. of CD vote shares		(4) Bins: Wtd-avg. of CD vote shares	
US tariff shock × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$)	-0.489	[0.256]	-0.522	[0.267]	0.125	[0.043]	0.129	[0.043]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)	-0.071	[0.041]	-0.074	[0.041]	-0.058	[0.086]	-0.053	[0.087]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)	-0.015	[0.024]	-0.011	[0.025]	0.023	[0.040]	0.024	[0.040]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)	0.025	[0.011]	0.025	[0.012]	0.002	[0.018]	0.001	[0.018]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)	-0.007	[0.008]	-0.007	[0.008]	0.010	[0.011]	0.009	[0.011]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.7, 1]$)	-0.006	[0.005]	-0.005	[0.005]	-0.016	[0.007]	-0.015	[0.006]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$)	-0.006	[0.022]	-0.015	[0.021]	-0.169	[0.084]	-0.186	[0.122]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)	0.017	[0.074]	0.022	[0.077]	-0.164	[0.083]	-0.191	[0.088]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)	-0.072	[0.038]	-0.078	[0.046]	-0.037	[0.014]	-0.043	[0.013]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)	-0.030	[0.021]	-0.030	[0.022]	-0.023	[0.035]	-0.027	[0.038]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)	0.006	[0.013]	0.005	[0.013]	-0.032	[0.024]	-0.032	[0.027]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.7, 1]$)	0.009	[0.009]	0.008	[0.009]	0.011	[0.013]	0.005	[0.012]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$)			0.528	[0.299]			6.632	[27.554]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)			0.172	[0.193]			0.585	[0.359]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)			0.209	[0.154]			0.205	[0.106]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)			-0.037	[0.038]			-0.033	[0.036]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)			-0.003	[0.007]			0.005	[0.008]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.7, 1]$)			-0.001	[0.004]			0.000	[0.006]
Health insurance share (2013-17 avg.)	-0.023	[0.098]	-0.026	[0.098]	0.294	[0.090]	0.291	[0.091]
Δ Health insurance share (2013-17 minus 2008-12)	0.041	[0.080]	0.047	[0.080]	-0.234	[0.094]	-0.229	[0.097]
Lag Δ Rep. House vote share (2016 minus 2014)	-0.287	[0.091]	-0.282	[0.093]	-0.454	[0.088]	-0.455	[0.089]
Lag Δ Rep. House vote share (2014 minus 2012)	-0.102	[0.042]	-0.099	[0.042]	-0.200	[0.041]	-0.200	[0.042]
Main effects: $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$),...	Y		Y		Y		Y	
Double interactions: Ag. subsidy × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$),...	Y		Y		Y		Y	
County initial controls and pre-trends	Y		Y		Y		Y	
State FEs	Y		Y		Y		Y	
Observations	2,633		2,633		3,011		3,011	
R^2	0.820		0.822		0.699		0.701	

Notes: Columns 1 and 3 follow the specification in Table 2, Column 2, while Columns 2 and 4 follow Table 2, Column 3. In Columns 1-2, the sample drops counties that are split across multiple CDs. In Columns 3-4, the 2016 competitiveness bins are constructed as a weighted-average of CD-level Republican two-party vote shares in the 2016 presidential election; for each county, this takes an average of the CD-level vote share across all CDs that overlap with the county in question, using the total number of votes cast for the Republican and Democratic parties in the 2016 House elections at the county-by-CD level as weights. Standard errors are two-way clustered by state and commuting zone.

Table A.4: Robustness: Alternative Tariff Shock Measures

Dep. variable:	Δ Republican House vote share (2018-2016)							
	(1) Incl. Rest-of-CZ tariff shocks		(2) Incl. Rest-of-CZ tariff shocks		(3) Full trade value tariff shocks		(4) Full trade value tariff shocks	
Panel A: Average Effect of Tariff Shock								
US tariff shock	0.006	[0.009]	0.006	[0.009]	0.002	[0.002]	0.002	[0.001]
Retaliatory tariff shock	-0.030	[0.014]	-0.035	[0.014]	-0.009	[0.004]	-0.011	[0.004]
Retaliatory tariff shock × Ag. subsidy			0.015	[0.006]			0.003	[0.002]
Ag. subsidy			-0.000	[0.007]			0.004	[0.007]
Rest-of-CZ US tariff shock	-0.004	[0.016]	-0.004	[0.016]				
Rest-of-CZ Retaliatory tariff shock	-0.011	[0.019]	-0.014	[0.020]				
Rest-of-CZ Retaliatory tariff shock × Ag. subsidy			0.018	[0.014]				
Health insurance share (2013-17 avg.)	0.259	[0.092]	0.255	[0.093]	0.265	[0.092]	0.259	[0.093]
Δ Health insurance share (2013-17 minus 2008-12)	-0.226	[0.100]	-0.223	[0.100]	-0.248	[0.108]	-0.245	[0.108]
Lag Δ Rep. House vote share (2016 minus 2014)	-0.456	[0.091]	-0.456	[0.091]	-0.449	[0.090]	-0.450	[0.089]
Lag Δ Rep. House vote share (2014 minus 2012)	-0.210	[0.042]	-0.209	[0.042]	-0.201	[0.041]	-0.201	[0.041]
Republican Presidential vote share (2016)	-0.058	[0.037]	-0.057	[0.037]	-0.066	[0.039]	-0.066	[0.039]
County initial controls and pre-trends	Y		Y		Y		Y	
State FEs	Y		Y		Y		Y	
Observations	2,956		2,956		3,011		3,011	
R^2	0.677		0.678		0.675		0.675	
Panel B: Heterogeneous Effects by Competitiveness Bins								
US tariff shock × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$)	0.159	[0.060]	0.164	[0.061]	0.017	[0.010]	0.017	[0.010]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)	-0.061	[0.090]	-0.059	[0.091]	-0.004	[0.010]	-0.004	[0.010]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)	-0.030	[0.035]	-0.027	[0.036]	0.001	[0.005]	0.002	[0.005]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)	0.018	[0.022]	0.017	[0.022]	0.005	[0.003]	0.005	[0.003]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)	-0.003	[0.010]	-0.002	[0.010]	-0.002	[0.002]	-0.001	[0.002]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.7, 1]$)	-0.002	[0.006]	-0.002	[0.006]	-0.000	[0.001]	-0.000	[0.001]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$)	-0.057	[0.057]	-0.055	[0.057]	-0.025	[0.016]	-0.025	[0.017]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)	-0.039	[0.080]	-0.047	[0.087]	-0.012	[0.021]	-0.015	[0.023]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)	-0.152	[0.073]	-0.175	[0.086]	-0.042	[0.011]	-0.045	[0.012]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)	-0.011	[0.029]	-0.011	[0.029]	-0.005	[0.006]	-0.005	[0.006]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)	-0.003	[0.015]	-0.006	[0.017]	0.002	[0.004]	0.001	[0.004]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.7, 1]$)	-0.008	[0.008]	-0.010	[0.008]	-0.002	[0.002]	-0.002	[0.002]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$)			0.044	[0.299]			0.039	[0.070]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)			0.217	[0.169]			0.053	[0.030]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)			0.532	[0.232]			0.101	[0.039]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)			-0.029	[0.041]			-0.012	[0.009]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)			-0.011	[0.009]			-0.001	[0.001]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.7, 1]$)			0.006	[0.005]			0.000	[0.001]
Health insurance share (2013-17 avg.)	0.292	[0.101]	0.293	[0.101]	0.298	[0.094]	0.296	[0.092]
Δ Health insurance share (2013-17 minus 2008-12)	-0.217	[0.095]	-0.217	[0.095]	-0.254	[0.108]	-0.255	[0.109]
Lag Δ Rep. House vote share (2016 minus 2014)	-0.450	[0.085]	-0.448	[0.085]	-0.447	[0.085]	-0.446	[0.085]
Lag Δ Rep. House vote share (2014 minus 2012)	-0.198	[0.040]	-0.196	[0.040]	-0.195	[0.039]	-0.194	[0.039]
Main effects: $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$),...	Y		Y		Y		Y	
Double interactions: Ag. subsidy × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$),...	Y		Y		Y		Y	
Double interactions: Rest-of-CZ US tariff shock × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$),...	Y		Y		N		N	
Double interactions: Rest-of-CZ Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$),...	Y		Y		N		N	
Triple interactions: Rest-of-CZ Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$),...	N		Y		N		N	
County initial controls and pre-trends	Y		Y		Y		Y	
State FEs	Y		Y		Y		Y	
Observations	2,956		2,956		3,011		3,011	
R^2	0.707		0.708		0.700		0.702	

Notes: Columns 1 and 3 follow the specification in Table 2, Column 2, while Columns 2 and 4 follow Table 2, Column 3. In Panel A, Column 1 controls additionally for the Rest-of-CZ US and retaliatory tariff shocks, namely: the tariff shocks experienced in the rest of the commuting zone, excluding the county in question. Column 2 further includes the interaction between the Rest-of-CZ retaliatory tariff shock and the county-level Ag. subsidy. In Panel B, Column 1 controls additionally for the Rest-of-CZ US and retaliatory tariff shocks interacted with the 2016 presidential vote competitiveness bin dummies. Column 2 further includes the triple interaction terms between the Rest-of-CZ retaliatory tariff shock, the county-level Ag. subsidy, and the competitiveness bin dummies. None of the Rest-of-CZ US or retaliatory tariff shock double or triple interaction coefficients in Panel B are statistically significant; these are not reported to save space. Columns 3 and 4 use county-level US and retaliatory tariff shocks measures that are constructed using the full value of trade flows affected, rather than the tariff rate multiplied by the value of trade. All alternative tariff shock measures are in units of $1,000 per worker. Standard errors are two-way clustered by state and commuting zone.

Table A.5: Health Insurance Effects by 2016 Presidential Vote Competitiveness Bins

Dep. variable: Δ **Republican House vote share (2018-2016)**	(1)		(2)	
US tariff shock × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$)	0.103	[0.066]	0.105	[0.067]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)	-0.022	[0.070]	-0.020	[0.072]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)	-0.005	[0.035]	-0.000	[0.035]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)	0.023	[0.020]	0.023	[0.020]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)	-0.005	[0.009]	-0.005	[0.009]
US tariff shock × $\mathbf{1}$(Pres. vote $\in (0.7, 1]$)	-0.004	[0.006]	-0.004	[0.006]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$)	-0.092	[0.064]	-0.094	[0.066]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)	-0.045	[0.085]	-0.055	[0.092]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)	-0.173	[0.042]	-0.185	[0.047]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)	0.001	[0.028]	0.001	[0.028]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)	-0.001	[0.015]	-0.004	[0.017]
Retaliatory tariff shock × $\mathbf{1}$(Pres. vote $\in (0.7, 1]$)	-0.005	[0.008]	-0.006	[0.007]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$)			0.249	[0.412]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)			0.190	[0.168]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)			0.472	[0.174]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)			-0.054	[0.035]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)			-0.012	[0.008]
Retaliatory tariff shock × Ag. subsidy × $\mathbf{1}$(Pres. vote $\in (0.7, 1]$)			0.002	[0.005]
Health insurance share (2013-17 avg.)	0.304	[0.098]	0.304	[0.096]
Δ Health insurance share (2013-17 minus 2008-12) × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$)	-0.184	[0.454]	-0.185	[0.454]
Δ Health insurance share (2013-17 minus 2008-12) × $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)	-0.262	[0.450]	-0.259	[0.450]
Δ Health insurance share (2013-17 minus 2008-12) × $\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)	-0.187	[0.266]	-0.192	[0.267]
Δ Health insurance share (2013-17 minus 2008-12) × $\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)	-0.849	[0.241]	-0.846	[0.239]
Δ Health insurance share (2013-17 minus 2008-12) × $\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)	-0.180	[0.121]	-0.172	[0.123]
Δ Health insurance share (2013-17 minus 2008-12) × $\mathbf{1}$(Pres. vote $\in (0.7, 1]$)	-0.086	[0.144]	-0.097	[0.140]
Lag Δ Rep. House vote share (2016 minus 2014)	-0.448	[0.089]	-0.447	[0.090]
Lag Δ Rep. House vote share (2014 minus 2012)	-0.195	[0.041]	-0.193	[0.041]
Main effects: $\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$),...	Y		Y	
Double interactions: Ag. subsidy × $\mathbf{1}$(Pres. vote $\in [0, 0.3]$),...	Y		Y	
County initial controls and pre-trends	Y		Y	
State FEs	Y		Y	
Observations	3,011		3,011	
R^2	0.702		0.703	

Notes: Column 1 builds on the specification in Table 2, Panel B, Column 2, while Column 2 builds on Table 2, Panel B, Column 3. Relative to Table 2, the above includes a full set of interaction terms between the change in health insurance coverage (2013-17 average minus 2008-12 average, from the American Community Survey) and the 2016 presidential vote share competitiveness bins. Standard errors are two-way clustered by state and commuting zone.

Table A.6: Explaining the Tariff Shock Measures: Replicating FGKK

Panel A **Dep. variable: US Tariff Shock**	(1) Full sample		(2) Full sample		(3) Full sample		(4) Close states	
$\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)	0.031	[0.037]	0.011	[0.012]	0.025	[0.018]	0.041	[0.032]
$\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)	0.042	[0.034]	0.005	[0.015]	0.021	[0.021]	0.008	[0.039]
$\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)	0.089	[0.043]	0.013	[0.018]	0.036	[0.027]	0.045	[0.049]
$\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)	0.101	[0.042]	0.000	[0.021]	0.023	[0.027]	0.023	[0.048]
$\mathbf{1}$(Pres. vote $\in (0.7, 1]$)	0.098	[0.038]	-0.010	[0.025]	0.009	[0.029]	-0.002	[0.059]
Employment share, Agriculture (2016)			-0.331	[0.110]	-0.333	[0.129]	-0.071	[0.246]
p-value, $(0.5, 0.6]$ vs. $(0.7, 1]$ bin coefficients	[0.697]		[0.188]		[0.082]		[0.103]	
County initial controls and pre-trends	N		FGKK		BBC		BBC	
Observations	3,113		3,097		3,097		1,092	
R^2	0.030		0.356		0.370		0.477	

Panel B **Dep. variable: Retaliatory Tariff Shock**	(1) Full sample		(2) Full sample		(3) Full sample		(4) Close states	
$\mathbf{1}$(Pres. vote $\in (0.3, 0.4]$)	0.013	[0.010]	0.017	[0.012]	0.010	[0.010]	0.016	[0.010]
$\mathbf{1}$(Pres. vote $\in (0.4, 0.5]$)	0.025	[0.008]	0.028	[0.012]	0.016	[0.010]	0.013	[0.011]
$\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$)	0.071	[0.015]	0.046	[0.018]	0.040	[0.014]	0.035	[0.015]
$\mathbf{1}$(Pres. vote $\in (0.6, 0.7]$)	0.058	[0.012]	0.040	[0.011]	0.032	[0.011]	0.030	[0.016]
$\mathbf{1}$(Pres. vote $\in (0.7, 1]$)	0.078	[0.013]	0.041	[0.012]	0.024	[0.013]	0.031	[0.016]
Employment share, Agriculture (2016)			2.325	[0.422]	2.372	[0.394]	2.142	[0.492]
p-value, $(0.5, 0.6]$ vs. $(0.7, 1]$ bin coefficients	[0.738]		[0.684]		[0.144]		[0.762]	
County initial controls and pre-trends	N		FGKK		BBC		BBC	
Observations	3,113		3,097		3,097		1,092	
R^2	0.048		0.402		0.445		0.468	

Notes: The dependent variable in Panel A is our US tariff shock measure, while that in Panel B is our retaliatory tariff shock measure, both in units of $1,000 per worker. All estimates are from least squares regressions, with observations weighted by total county population in 2016. The key explanatory variables are indicators for the county-level two-party Republican vote share in the 2016 Presidential Election. Column 2 includes the "FGKK" set of controls (reconstructed as best we can): employment shares in agriculture and manufacturing in 2016 (from the County Business Patterns), together with pre-trends between 2013-2016; the unemployment rate, and log mean household income in 2013-2017 (five-year averages from the American Community Survey), together with pre-trends between 2008-2012 and 2013-2017; the white population share in 2016 (from the US Census), and the share with some college education in 2013-2017 (from the American Community Survey). Columns 3 and 4 include the full "BBC" set of county initial controls and pre-trends used in Tables 2 and 3 in the main paper. Column 4 restricts the sample to 15 swing states: AZ, CO, FL, GA, IA, MI, MN, NC, NH, NM, NV, OH, PA. We further report the p-value of a two-sided coefficient test of equality for the coefficients of the $\mathbf{1}$(Pres. vote $\in (0.5, 0.6]$) and $\mathbf{1}$(Pres. vote $\in (0.7, 1]$) bins. Standard errors are clustered by state.