THE
ECONOMIC
JOURNAL

The Economic Journal, **131** (*May*), 1717–1741 DOI: 10.1093/ej/ueaa122

TARIFFS AND POLITICS: EVIDENCE FROM TRUMP'S TRADE WARS*

Thiemo Fetzer and Carlo Schwarz

We use the recent trade escalation between the USA and its trade partners to study whether retaliatory tariffs are politically targeted. We find comprehensive evidence using individual and aggregate voting data suggesting that retaliation is carefully targeted to hurt Trump. We develop a simulation approach to construct counterfactual retaliation responses allowing us to quantify the extent of political targeting while also studying potential trade-offs. China appears to place great emphasis on achieving maximal political targeting. The EU seems to have been successful in maximising political targeting while at the same time minimising the potential damage to its economy.

'Trade wars are good, and easy to win.' Based on this assertion, President Donald Trump announced on 1 March 2018 that the USA would impose a 25% tariff on steel and a 10% tariff on aluminium imports. Initially exempt, Canada, Mexico and the EU became subject to the steel and aluminium tariffs from 31 May 2018. Additionally, the Trump administration set a tariff of 25% on 818 categories of goods imported from China worth $50 billion on 6 July. Despite Trump's claims, the dispute involving China, the European Union (EU), Canada and Mexico escalated, with reciprocal tariffs being imposed on imports from the USA. Anecdotal evidence suggests that these retaliatory tariffs were chosen in a way to maximise political pressure on the USA (Chan and Smale, 2018). The EU, for example, imposed tariffs on iconic American brands like Harley-Davidson motorbikes, which are produced in Wisconsin, the home state of then Speaker of the House Paul Ryan. While this is suggestive, so far we know little about how countries design their retaliatory tariffs, as few trade disputes reach a stage of escalation in which threatened tariffs are actually imposed or retaliation measures are triggered. This paper fills this gap by investigating the degree to which retaliation by the USA's trade partners was politically targeted. Furthermore, we evaluate the extent to which countries and trading blocks optimise trade-offs when designing a retaliation response.

In the first part of the paper, we ask whether the retaliatory tariffs are designed to target Trump's voter base. We document that retaliatory tariffs are distinctly targeted towards areas that supported Trump in the 2016 election. To assess the degree of political targeting, we construct a county-specific retaliation exposure measure similar to Autor *et al.* (2013) using data on US exports. Based on this exposure measure, we find that retaliatory tariffs target areas that

* Corresponding author: Thiemo Fetzer, Department of Economics, University of Warwick, Coventry CV4 7AL, UK. Email: t.fetzer@warwick.ac.uk

This paper was received on 12 March 2020 and accepted on 8 October 2020. The Editor was Hans-Joachim Voth.

The data and codes for this paper are available on the Journal website. They were checked for their ability to reproduce the results presented in the paper. The authors were granted an exemption to publish parts of their data because access to these data is restricted. However, the authors provided the Journal with temporary access to the data, which enabled the Journal to run their codes. The codes for the parts subject to exemption are also available on the Journal website. The restricted access data and these codes were also checked for their ability to reproduce the results presented in the paper.

We would like to thank the anonymous referees and an anonymous source in the EU Commission, as well as Mirko Draca, Massimo Morelli, Dennis Novy and Debraj Ray for their helpful comments. Financial support from the ESRC CAGE research centre and a UKRI Open Access grant is gratefully acknowledged.

swung to Trump in the 2016 presidential election. In contrast, areas that swung behind other Republican candidates in the House or Senate elections held on the same day were not the targets of retaliatory tariffs. Our estimates suggest that those areas most exposed to retaliatory tariffs from China exhibited an up to 5% greater swing to Trump relative to the performance of the 2012 Republican candidate. Using individual-level opinion polling data, we show that even among self-identifying Republicans, retaliation appears to be distinctly targeted towards areas in which Republicans favoured Donald Trump over other Republican contestants for the 2016 presidential nomination. Furthermore, we document that the degree of political targeting appears to pick up a distinct shift in geographic patterns of Republican party affiliation—but only after Donald Trump entered the 2016 presidential race in 2015. Last, we also draw on data from an individual-level panel dataset, which further corroborate these findings.

In the second part, we investigate both the feasibility of political targeting and the extent to which countries face trade-offs in their retaliation design: in particular, the harm retaliation may cause to their own economy. To do so, we propose a novel simulation approach. This simulation approach aims to approximate the choice set that each retaliating country faces. The approach works by drawing alternative feasible retaliation baskets that could have been chosen and that would produce a similar-sized retaliation response. For each of the simulated alternative baskets, we then construct our implied county-level retaliation exposure measure. Furthermore, we use the *revealed comparative advantage* index introduced by Balassa (1965) along with estimated trade elasticities to measure the likely effectiveness and also proxy for the likely economic pressure that a specific retaliation response implies for a retaliating trading bloc's own economy. In a similar vein, we construct a measure capturing the extent to which the USA is a dominant supplier of specific goods in a retaliation response. These measures allow us to evaluate whether there exist tangible trade-offs between higher degrees of political targeting and likely domestic economic harm due to retaliation.

In our analysis, we compare the actually chosen retaliation response to the counterfactual baskets. We observe that while both China and the EU are able to achieve a high degree of political targeting, only the EU appears to be specifically aiming to mitigate the harm to its own economy. In contrast, China seems unconcerned about retaliating against goods for which the USA has a high revealed comparative advantage or of which it is the main supplier. It is particularly remarkable that it would have been possible for China to retaliate with an alternative bundle, producing the same degree of political targeting, while likely producing less domestic economic damage.

Our results contribute to the literature on the political economy of protectionist trade policies. Economists have long studied the political economy underlying trade conflicts. Given the large literature on the welfare-enhancing effects of trade (e.g., Ricardo, 1891; Hecksher and Ohlin, 1933; Frankel and Romer, 1999; Baldwin, 2004, to name just a few), it is widely accepted that erecting tariff barriers, while able to help certain individual industries, is not only harmful to trading partners but also constitutes an act of self-harm (Bown, 2004; Breuss, 2004). To offer an explanation of why politicians nonetheless often favour tariffs, the imposition of domestic tariffs has been attributed to the influence of interest groups (Grossman and Helpman, 1994), people's inequity aversion (Lü *et al.*, 2012), the importance of tariffs as a source of revenue (Hansen, 1990) or the structure of consumer tastes (Baker, 2005), along with the relative factor endowments (Scheve and Slaughter, 2001). Existing research further suggests that democracies are more likely to lower tariff barriers, but are also more likely to protect their agricultural sectors and make use of non-tariff barriers (NTBs; e.g., Kono, 2006; Barari *et al.*, 2019). Cameron and Schuyler (2007) investigate the determinant of protectionism in the agricultural sector. In a closely related work, Gawande and Hansen (1999) investigate the deterrence effect of NTBs and how retaliatory NTBs can be used to reduce foreign trade barriers. Our findings shed light on how other countries react to protectionism and the USA's aggressive trade policy. To the best of our knowledge, we are the first to empirically document the trade-offs underlying retaliation design.

Recent work by Amiti *et al.* (2019) and Fajgelbaum *et al.* (2020) investigates the economic impact of Trump's trade war on US consumers. This paper is different in at least two dimensions. First, rather than focusing on the economic impact of tariffs, we aim to shed light on how trade partners respond to the USA's unilateral imposition of protectionist measures. Second, using a novel simulation approach, we can trace out the underlying trade-offs that countries or trading blocs navigate when designing a retaliation response. In this way, our paper provides new insights into the political economy of retaliatory tariffs.

Our paper also speaks to the political effects of trade integration. Building on the seminal work by Autor *et al.* (2013), a significant literature is emerging on the political implications of these economic shocks. Dippel *et al.* (2015), Autor *et al.* (2016), Che *et al.* (2017) and Colantone and Stanig (2018a,b) each document, in the context of the USA, the UK, Germany and Western Europe more broadly, that those areas most exposed to import competition saw a rise in populism or political polarisation. Feigenbaum and Hall (2015) use roll call data to show an impact on US trade policy: politicians from districts most exposed to the 'China-shock' shifted to vote in a more protectionist direction on trade-related bills. Autor *et al.* (2016) and Che *et al.* (2017) suggest that the election of Donald Trump, on a nativist 'America First' platform, was significantly influenced by votes coming from areas that suffered most acutely from import competition with low-income countries. This paper studies the flip-side of the story and looks at whether retaliatory tariffs are aimed at counties or parts of the USA with tradable-goods-producing sectors that have survived the 'China shock'.

In other related research, economists have analysed the economic and political targeting of sanctions (e.g., Eaton and Engers, 1992; Elliott and Hufbauer, 1999; Ahn and Ludema, 2017). Kavaklí *et al.* (2020) find that comparative advantage in exports and domestic production capabilities determines a country's ability to minimise costs while maximising its power to hurt in the context of economic sanctions. While tariffs have been studied mainly as an economic tool, sanctions have been understood as a political tool to induce compliance. In this literature, Marinov (2005) and Allen (2008) provide evidence that sanctions increase the probability of leadership change. In other work, Draca *et al.* (2018) show that US sanctions against Iran have been effective in targeting politically connected firms and actors. Despite the fact that compared to sanctions, retaliatory tariffs are far more limited in scope and intensity, our findings suggest that retaliatory tariffs are also used as a political tool.

The rest of the paper proceeds as follows. Section 1 describes the political context and the data used in the empirical analysis. Section 2 shows the extent of political targeting of tariffs. Section 3 introduces our simulation approach and provides evidence for the trade-off between political targeting and domestic harm. Section 4 concludes.

1. Context and Data

The international trading system after the Second World War was first institutionalised through the General Agreement on Tariffs and Trade (GATT) in 1948. This was a direct result of the failings of the international trade system during the Great Depression. In 1930 the Smoot-Hawley Act had increased tariffs on more than 20,000 products imported by the USA. This had set off a tit-for-tat retaliation. Irwin (1998) estimates that nearly a quarter of the observed 40% decline in imports can be attributed to the rise in US tariffs in this period, and that these tariffs thereby contributed to the lengthening of the Great Depression.

Through multiple GATT rounds from 1948 onwards, average tariff rates were reduced significantly. One of the most important features of the international trading system, which is now regulated by the WTO—the successor organisation to the GATT, established in 1995—is a formal Dispute Resolution System. In principle, governments are still able to restrict trade to foster non-economic social policy objectives, to ensure 'fair competition', or to support the preferential treatment of developing countries, regional free-trade areas and customs unions. But measures of this kind are subject to scrutiny, are expected to adhere to the broad principles of the WTO and can be contested by WTO member countries by invoking the WTO's Dispute Resolution mechanism. Rosendorff (2005) and Sattler *et al.* (2014) provide evidence that the WTO's Dispute Resolution mechanism helps to enforce stable trade relationships. The Dispute Resolution mechanism also regulates the imposition of retaliation measures.

1.1. *Retaliatory Tariffs as a Political Tool*

The most recent occasion on which the international trading system came close to a similar escalation was the imposition of steel tariffs by President George W. Bush, which took effect on 30 March 2003. The USA justified these tariffs as an anti-dumping response, and in contrast to the current situation, NAFTA partners were exempted from the tariffs. The EU and other trading blocs immediately filed a dispute with the WTO. On 11 November 2003, this resulted in a verdict against the USA, and the tariffs were abolished on 4 December 2003. The WTO ruling implied that the anti-dumping justification for the tariffs was void, as the USA had in fact been importing less steel compared to 2001 and 2002. The ruling authorised more than \$2 billion in sanctions against the USA. President Bush initially wanted to preserve the tariffs. Following threats of retaliation by the European Union, however, the USA backed down and withdrew the tariffs.

While this does not prove that the threat of retaliation was the reason why tariffs were abandoned, it does suggest that this may have played a role. The European Commission stands out in terms of transparency regarding the objectives it aims to achieve in the context of trade disputes (see Stasavage, 2004; Baccini, 2010 on the role of transparency). Specifically, EU Regulation 654, published in 2014, outlines three objectives for commercial policy measures in the context of a trade dispute:

> 'Commercial policy measures . . . shall be determined on the basis of the following criteria, in light of available information and of the Union's general interest:
> (a) effectiveness of the measures in inducing compliance of third countries with international trade rules;
> (b) potential of the measures to provide relief to economic operators within the Union affected by third country measures;
> (c) availability of alternative sources of supply for the goods or services concerned, in order to avoid or minimise any negative impact on downstream industries, contracting authorities or entities, or final consumers within the Union.'

In other words, trade policy should aim to change the trade policy of the opposing country, while minimising harm to the bloc's own economy.

To design the retaliation response, the European Commission is known to use an algorithm to select products against which retaliatory tariffs are targeted. This algorithm is naturally a closely guarded secret.[1]

The Chinese government does not publish its policy objectives in the trade dispute, but there is evidence that it is also attempting to target its tariffs against the electoral base of Donald Trump and the Republican Party. For example, the Chinese as well as the EU's retaliation targeted bourbon whiskey produced in Kentucky, the home state of Senate majority leader Mitch McConnell. Also, the Wisconsin congressional district of former Speaker of the House Paul Ryan was targeted with retaliatory tariffs on cranberries and cranberry products. Moreover, China and Mexico targeted pork and soybeans, which disproportionately affected Iowa, the home state of influential Republican Senate Agriculture Committee member Senator Charles E. Grassley. These examples suggest that the design of retaliatory tariffs shares some similarities with that of political sanctions. The growing literature on sanctions understands sanctions as a political tool to induce compliance (see, for example, Eaton and Engers, 1992; Elliott and Hufbauer, 1999; Ahn and Ludema, 2017). In contrast, the political dimensions of tariffs have so far been widely ignored. In our analysis, we investigate to what degree the retaliating countries have indeed systematically politically targeted their retaliation. For our analysis, we construct a measure of exposure to retaliatory tariffs for each US county, which we discuss next.

1.2. *Descriptives of the Retaliation Measures*

The retaliation measures against the US tariffs take the form of a list of products with descriptions and (typically) the Harmonized System (HS) code along with an (additional) tariff rate to be imposed on imports of these goods from the USA. These lists are prepared through a consultative process in the case of the EU and Canada. They are lodged and registered with the WTO, and there is typically a delay prior to the tariffs being implemented. For our analysis, we have obtained retaliatory tariff lists from the EU, China, Mexico and Canada. We are not analysing the retaliation of other countries, such as India and Turkey, as the overall trade volume and therefore the retaliation is far smaller.[2]

Online Appendix Figure A1 visualises the distribution of the retaliation measures across coarse economic sectors. The figure suggests that manufacturing sector outputs, as well as agricultural commodities, were significant features in the retaliation lists. We next describe how we use the retaliation lists to construct a county's exposure to tariffs.

1.3. *Measuring Exposure to Retaliation*

We use two data sources to construct a county-level measure of exposure to retaliation measures. First, we use data from the Brookings (2017) Export Monitor. These data contain a measure

[1] One of the authors of this paper had a conversation with an anonymous senior EU Commission source, who referred to the algorithm as the EU's 'weapon of war' in the context of the trade dispute, indicating why it is a closely guarded secret.

[2] The official retaliation lists are available here: EU: https://trade.ec.europa.eu/doclib/press/index.cfm?id=1842 (last accessed: 29 October 2020); China: http://english.mofcom.gov.cn/article/newsrelease/significantnews/201806/20180602757681.shtml (last accessed: 29 October 2020); Mexico: http://dof.gob.mx/nota_detalle.php?codigo=5525036&fecha=05/06/2018 (last accessed: 29 October 2020); Canada: https://web.archive.org/web/20190724035242/https://www.fin.gc.ca/activty/consult/cacsap-cmpcaa-eng.asp (last accessed: 18 August 2018).

of county-level exports across a set of 131 NAICS industries.[3] We denote as $X_{c,i}$ the export of industry i for each county c. The data also provide an estimate of the total exports at the county level and the number of export-dependent jobs.

Second, we use the individual retaliation lists $\mathcal{L}_r$ for $r \in \{EU, MX, CA, CN\}$. These are matched at the eight-digit HS level to the US trade data using export volume.[4] We validate our mapping by comparing the resulting value of trade flows affected by tariffs with the official WTO submissions. For this exercise, we make use of HS-level US import and export data from the US Census Bureau.[5] In the case of the EU, the retaliation measures officially target trade worth \$7.2 billion. Matching the EU list to the US trade data for 2017, we find that US exports worth \$7.6 billion are affected by retaliation, suggesting that the overall magnitude is similar.

To link the targeted exports to the different six-digit NAICS sectors that produce the goods (HS10 codes), we use the concordances between HS codes and NAICS/SIC codes from Schott (2008). These concordances provide up to ten-digit commodity codes, which map onto the Harmonized System codes used, together with SIC and NAICS codes. This allows us to merge the tariffs lists with the employment data. In case multiple sectors are linked to an HS10 code, we retain the NAICS sector listed first in the concordance. As an illustration, consider the example of the EU's rebalancing measures, which include the item '10059000 Maize (excluding seeds for growing)'. This HS code is mapped to the NAICS industry code 111150, which stands for 'Corn Farming'. This procedure results in a list of *tariff-exposed industries*.

Next, we collapse the total volume of affected trade to the four-digit industry level. This gives us a measure of total exports $T_{i,r}$, from four-digit industry i, which was affected by the retaliatory tariffs of country r. We break this measure down to the county level based on the share that the exports from county c makes up of all exports for goods attributed to industry i. Let $X_{c,i}$ denote the exports from county c in industry i. The share is then given as $\frac{X_{c,i}}{\mathbf{X}_i}$, where $\mathbf{X}_i = \sum_c X_{c,i}$. The product $\frac{X_{c,i}}{\mathbf{X}_i} \times T_{i,r}$ provides the volume of exports stemming from county c and industry i that is subject to retaliation. We aggregate this measure up across all industries i to arrive at the total value of exports from county c subject to retaliation from retaliation list r. In the last step, this measure is normalised by the total value of exports from county c as $\mathbf{X}_c = \sum_i X_{c,i}$.[6]

The final exposure measure $\tau_{c,r}$ for county c and list of retaliatory tariffs r is given as:

$$\tau_{c,r} = \frac{\sum_i \frac{X_{c,i}}{\mathbf{X}_i} \times T_{i,r}}{\mathbf{X}_c}.$$

These measures approximate the exposure of counties to retaliation measures of each retaliating country r. The measure is bounded between 0 and 1. If industries in a county are unaffected by tariffs, the measure is 0. If the entire production of a good subject to retaliation were to take place

[3] This source incorporates a host of data, including US goods trade data, service sector export data from the Bureau of Economic Analysis (BEA), Internal Revenue Service (IRS) data for royalties, Moody's Analytics production estimates at the county level and foreign students' expenditures from NAFSA. More details on Brookings (2017) can be found here: https://www.brookings.edu/research/export-nation-2017/ (last accessed: 29 October 2020).

[4] While technically the codes of products are provided at the ten-digit level, the matching results are best at the eight-digit level due to slight discrepancies in the coding standard across countries. This introduces only a small amount of inconsequential noise.

[5] These data can be found here: https://usatrade.census.gov/ (last accessed: 29 October 2020).

[6] In Online Appendix Table A2 we show that the results also hold when we normalise our measure by population instead.

in a single county and if that county were to export only this good, the exposure measure would be 1.

Our approach is similar to the Autor *et al.* (2013)-type labour market shocks. The main difference is that rather than constructing this measure based on sector-level employment figures, our measure is based on sector-level output figures. This should come closer to capturing the economic impact more broadly. As a robustness check, we consider an alternative exposure measure based on Autor *et al.* (2013) and Kovak (2013), which uses the County Business Patterns (CBP) employment data to construct a county-level retaliation exposure based on sector-level employment shares. In Online Appendix Table A1 we show that results are similar when using this alternative measure.[7]

Since the added tariff rate was set at 25% for 85% of the products, our retaliation exposure measure ignores the actual added tariff rate. This also implies that the variation in our county-level exposure measure $\tau_{c,r}$ is driven by the *choice of products* and not the choice of tariff rates. While this is only a small deviation from the actual data, it greatly simplifies the simulation of counterfactual retaliation baskets in Section 3. In Online Appendix Figure A2 we compare our exposure measure with the exposure measure that would result if we incorporated the actual added tariff rate. The two measures are statistically virtually identical.

1.4. *Main Political Outcome Measures*

In the following, we describe the aggregate and individual-level data sources used to measure the extent of political targeting.

Aggregate election results: We leverage election results data collated by Dave Leip. These data provide us with county-level election outcomes, specifically for the recent 2008, 2012 and 2016 presidential elections, the House and Senate elections, and the 2018 midterm elections. While the natural resolution for House election is the congressional district level, unfortunately, our retaliatory tariff exposure measure is not available at the congressional district level.

Gallup Daily Tracker: We make use of the Gallup Daily Tracker data from 2012 covering the period up to mid 2018. The data are a repeated cross section containing the county of residence of individual respondents. Our primary focus is on three types of measures: the individual-level party affiliation, the presidential approval rating and the expressed support for the candidates in the 2016 election. These data are particularly useful, as the underlying samples are large enough to study how the correlation between an individual's Republican Party identity and the county-level exposure to retaliation evolved over time. As the underlying microdata do not provide information on actual voting or voting intention, we use an additional individual-level data set with a quasi-panel structure.

Cooperative Congressional Election Study: The Cooperative Congressional Election Study (CCES) is a large survey that consists of two waves in election years comprising a pre- and a post-election wave (see Ansolabehere and Rivers, 2013 for more detail). The survey around the 2016 presidential election also asked how individuals voted in the preceding 2012 presidential election. This allows us to study the data in first-difference to shed some light on whether retaliation appears targeted towards areas that saw swings in political support. Furthermore, the CCES makes it possible to narrow down the set of respondents who voted based on the national

[7] This is not surprising, as under certain assumptions on the production functions, the measures would be identical.

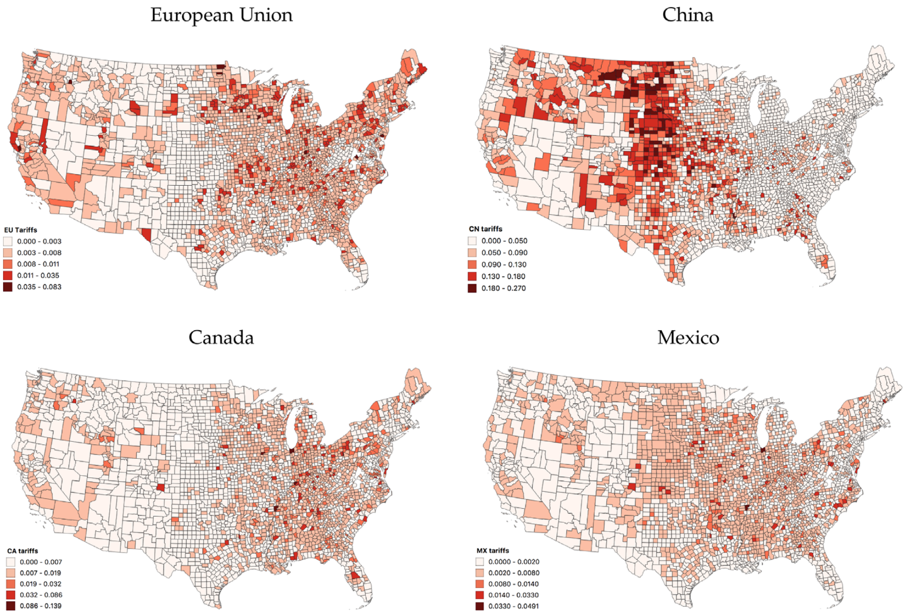

Fig. 1. *Distribution of Share of County-Level Export Trade Volumes Affected by Retaliation Measures by the EU, China, Canada and Mexico.*
Notes: The map plots the quintiles of the measure of county-level exposure to retaliation from the respective countries. The construction of the exposure measure is described in more detail in Subsection 1.3.

voter file of over 180 million records (see Enamorado and Imai, 2018 for a description of the method).

While the primary focus of this paper is to show that retaliation is carefully politically calibrated, the trade war and retaliation also do have pure economic effects. In related work, Amiti *et al.* (2019) and Fajgelbaum *et al.* (2020) study the implication of the trade war on consumer welfare and prices. In Section 2 of the Online Appendix we provide some auxiliary evidence that complements their work, suggesting that retaliation has indeed been effective in reducing US exports and has led to a drop in export prices, suggesting that exposure to retaliation has produced an economic shock.

2. Was the Retaliation Politically Targeted?

2.1. *Descriptive Evidence*

We first provide descriptive evidence that counties with stronger support for the Republican Party were more heavily targeted by tariffs. Figure 1 plots the retaliation exposure from the different trading partners for each US county. The figure highlights that the retaliatory tariffs from China, the EU, Canada and Mexico affected different counties. Furthermore, Panels (a) and (b) of Figure 2 suggest a clear pattern whereby counties with a stronger leaning towards the Republican Party were more heavily targeted by tariffs. The same holds true for counties that saw a bigger swing to Trump in the 2016 presidential election. We explore this further in a regression framework.

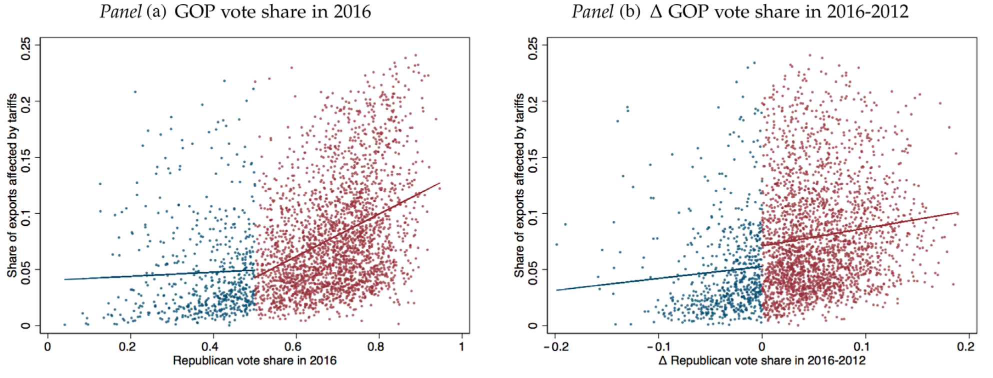

Fig. 2. *County-Level Export Share Exposed to Tariffs and Republican Vote Share. Panel (a): Republican vote share in 2016. Panel (b): Change in Republican vote share, 2016–2012.*
Notes: The figure plots the Republican Party vote share in the 2016 presidential election on the horizontal axis in Panel (a) and the change in the Republican Party vote shares between the 2016 and 2012 presidential elections at the county level in Panel (b) against the overall share of each county's exports that are exposed to retaliation by all countries.

2.2. *County-Level Data*

Empirical specification: To determine to what extend retaliatory measures disproportionately targeted Republican counties within the USA, we estimate the following regression equation:

$$y_{c,s} = \alpha_s + \beta_r \times \tau_{c,r} + \epsilon_c. \tag{1}$$

In this specification $y_{c,s}$ measures the vote share of the Republican Party in county c in state s in 2016. As an alternative outcome we use $\Delta y_{c,s}$, the change in the Republication Party vote share between the 2012 presidential election and the 2016 presidential election at the county level. $\tau_{c,r}$ is the county-level exposure measure for retaliatory tariffs list r (for more details see Subsection 1.3). All regressions include state fixed effects, hence we exploit within-state variation in retaliation exposure. Standard errors are clustered at the county level.[8]

Results: The results from the estimation of model (1) are presented in Table 1. The results suggest that counties that are more exposed to retaliatory tariff had higher levels of support for Trump in the 2016 presidential election. Furthermore, as indicated in Panel (b), counties exposed to retaliation also saw larger swings in support from the 2012 presidential election to the 2016 presidential election. The point estimate in column (2) suggests that the counties most exposed to EU retaliation saw an average swing in the Republican candidates' vote share of 22% vis-à-vis counties not exposed to EU retaliation.

As the retaliation exposure measures $\tau_{c,r}$ are bounded between zero and one, the coefficients are directly comparable. We find that the degree of political targeting is strongest for the EU's and Mexico's retaliations. We will revisit this result in our simulation study in Section 3. Before turning to the individual-level data, we next conduct further robustness checks for our baseline findings.

Robustness: We first explore whether the targeting was stronger for the presidential election than for the House and Senate elections held on the same day (Tuesday 8 November 2016). The

[8] We show that our main results are robust to alternative levels of clustering as well as to Conley standard errors in Online Appendix Table A4.

Table 1. *Measuring Degree of Political Targeting of Retaliation Measures Studying Republican Electoral Performance in 2016.*

	(1)	(2)	(3)	(4)	(5)
		Retaliatory tariffs imposed by . . .			
	Combined	CN	EU	CA	MX
Panel (a): 2016 GOP vote share					
Retaliation exposure	2.459 ***	3.083***	7.773***	2.314**	7.869**
	(0.233)	(0.209)	(1.508)	(1.120)	(3.815)
Observations	3,104	3,104	3,104	3,104	3,104
Clusters	3,104	3,104	3,104	3,104	3,104
Mean of DV	0.458	0.458	0.458	0.458	0.458
Panel (b): ΔGOP vote share, 2016–2012					
Retaliation exposure	0.750***	0.891***	2.598***	0.880***	2.885***
	(0.054)	(0.057)	(0.368)	(0.239)	(0.833)
Observations	3,063	3,063	3,063	3,063	3,063
Clusters	3,063	3,063	3,063	3,063	3,063
Mean of DV	−0.0137	−0.0137	−0.0137	−0.0137	−0.0137
State FE	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is either the Republican vote share in 2016 in Panel (a) or the change in Republican vote share between 2016 and 2012 in Panel (b). All regressions include state fixed effects. Counties are weighted by county-level population. Standard errors are clustered at the county level and are presented in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

results of this exercise can be found in Online Appendix Table A3. Panel (a) explores Republican Party vote shares. Throughout, there is a strong positive correlation—yet we find no evidence for differences in targeting across election types. In Panel (b) we compare the changes in Republican candidate vote share from the elections held in 2012 (for presidential and House elections). For the Senate election we compare the change with the most recent prior election for Senators (as only one-third of Senators are up for election each time). In this specification it appears that the regression coefficient for retaliation exposure is markedly larger for the presidential election but not for Republican candidates across other election types. This holds true despite the fact that voters could vote *on the same day in 2016*. This provides some additional evidence that retaliation may have been targeted to hit areas that swung behind Trump in 2016. A potential rationale behind such a strategy could be that these voters may conceivably swing back (see Alesina and Rosenthal, 1995; 2006 or Scheve and Tomz, 1999 for work studying the dynamics of US presidential and midterm elections).

In Online Appendix Table A5 we highlight that the correlation between retaliation exposure and (shifts in) support of Republican presidential candidates is distinctly stronger for the 2016 election. We investigate this observation further in the individual level analysis. Our finding are similar when we use an alternative exposure measure based on the sector-level employment shares inspired by Autor *et al.* (2013; see Online Appendix Table A1).

Last, in Online Appendix Table A6 we show that our results are robust to the inclusion of additional control variables.[9] First, we control for a county-level measure of the China shock used in Autor *et al.* (2013). This control is motivated by the work of Autor *et al.* (2016), who find that Trump performed better in counties that were more exposed to Chinese import

[9] Note that we focus on the combined retaliation exposure measure. The patterns are very similar when analysing country by country.

competition.[10] In line with this result, we find that the estimated coefficient on the China shock is positive and significant. Yet our retaliation exposure coefficient hardly changes. This is not surprising for two reasons. Naturally, a county's exposure to retaliation depends on the structure of trade between the USA and the trading partner. Retaliation exposure is driven by US exports, while the China shock is based on US imports. In addition, trade dispute–induced retaliation can produce economic shocks only in parts of the USA in which the tradable goods–producing sectors have survived the 'China shock'.[11] We also control for the level of (and changes in) turnout in the 2016 presidential election. Guiso *et al.* (2018) suggest that the ability for populist candidates to affect turnout may be a key factor in their success. Indeed, in Online Appendix Table A7 we document that places more exposed to retaliation saw, on average, lower levels of turnout. Yet our observation suggesting that retaliation was politically targeted remains intact.[12]

2.3. *Cross-Sectional Individual-Level Data*

We use repeated individual-level cross-sectional data from the Gallup Daily Tracker. This allows us to study the extent of support for Donald Trump using individual-level microdata allowing us to control for a set of potential confounders. Furthermore, we can exploit variation over time and draw comparisons with other Republican candidates.

Empirical specification: To leverage individual-level data, we modify our above regression specification in the following way:

$$y_{i,c,t} = \alpha_s + \nu' X_i + \beta_r \times \tau_{c,r} + \epsilon_c. \tag{2}$$

In this regression $y_{i,c,t}$ measures whether an individual i in county c in year t has a favourable view of Donald Trump as candidate. In our analysis we focus on the period from June 2015 to March 2016, prior to the election and prior to Donald Trump becoming the presumptive nominee. This allows us to compare the degree of targeting for other Republican candidates who were (still) in the race at the same time. The specification controls for state fixed effects α_s as well as a set of individual controls X_i. In particular, we control for the respondent's race across 5 categories, income across 12 categories, gender and the year of the survey. In specifications where the dependent variable is not party affiliation, we also control for an indicator whether a respondent describes themselves as Republican or leaning Republican.

Since the Republican Party affiliation is observed consistently from 2012 onwards, we can further estimate a flexible difference-in-difference specification:

$$y_{i,c,t} = \alpha_c + \gamma_t + \nu' X_i + \sum_{t=2012}^{2018} \beta_{r,t} \times \tau_{c,r} + \epsilon_c. \tag{3}$$

Since the regression contains county fixed effects α_c and time fixed effects γ_t, the coefficient $\beta_{r,t}$ captures the differential *changes* in individuals' leaning towards the Republican Party and our

[10] Similar effects have been documented in the context of the UK and Western Europe more broadly (Colantone and Stanig, 2018a,b); Feigenbaum and Hall (2015) shows that politicians from districts most exposed to the 'China shock' became more protectionist.

[11] This fact can also been seen in Online Appendix Figure A3, which shows that the relationship between tariff exposure and the China shock is negative.

[12] As an alternative way to address the concerns of committed county characteristics, we perform a matching exercise. The results of this exercise are reported in Online Appendix Tables A8 and A9.

Table 2. *Measuring Degree of Political Targeting Using Individual-Level Data from 2016 and 2017.*

	(1)	(2)	(3)	(4)	(5)
		Retaliatory tariffs imposed by . . .			
	Combined	CN	EU	CA	MX
Panel (a): Self-identified Republican					
Retaliation exposure	1.185***	1.423***	3.799***	1.225**	3.938**
	(0.114)	(0.107)	(0.828)	(0.572)	(1.798)
Observations	376,620	376,620	376,620	376,620	376,620
Counties	2,956	2,956	2,956	2,956	2,956
Mean of DV	0.421	0.421	0.421	0.421	0.421
Panel (b): Favourable view of Trump (candidate)					
Retaliation exposure	0.629***	0.738***	2.100***	0.533***	1.902***
	(0.062)	(0.080)	(0.500)	(0.181)	(0.537)
Observations	111,152	111,152	111,152	111,152	111,152
Counties	2,817	2,817	2,817	2,817	2,817
Mean of DV	0.335	0.335	0.335	0.335	0.335
GOP Party identification	Yes	Yes	Yes	Yes	Yes
Panel (c): Presidential approval for Trump					
Retaliation exposure	0.733***	0.909***	1.535***	0.651**	2.300**
	(0.067)	(0.065)	(0.463)	(0.293)	(0.989)
Observations	181,504	181,504	181,504	181,504	181,504
Counties	2,876	2,876	2,876	2,876	2,876
Mean of DV	0.412	0.412	0.412	0.412	0.412
GOP Party identification	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Race	Yes	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes
Gender	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is a dummy variable indicating whether a respondent is a Republican or leaning Republican in Panel (a); whether the respondent holds a favourable view of Donald Trump as a presidential candidate, asked from July 2015 until October 2016, in Panel (b); or whether they approve of Donald Trump's performance as president, asked from January 2017 until mid 2018, in Panel (c). The independent variable measures the county-level retaliation exposure to retaliation from the countries or trading blocks indicated in the column heads. Observations are weighted by the provided survey weights. Standard errors are clustered at the county level and are presented in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

county-level measure of retaliation exposure. In other words, $\beta_{r,t}$ picks up whether areas more exposed to retaliatory tariffs exhibited shifts in the support for the Republican Party relative to previous years. If retaliation was indeed targeted against counties with a Republican voter base that identifies with Donald Trump, we would expect the correlation between individual respondents' self-reported affinity for the Republican Party and the county-level retaliation exposure measure to increase with Trump's presidential run. Furthermore, this analysis will also show whether there were changes in Republican support before Trump's campaign started. In this way, we can disentangle general shifts in political preferences or party affiliation from support for Trump as a candidate.

Results: In Table 2 we show that retaliation is again highly correlated with measures of approval for Donald Trump both as candidate—Panel (a)—and as president—Panel (b). Retaliation is also much more likely to affect parts of the USA where respondents have an affinity towards the Republican Party, as shown in Panel (c). Consistent with the previous observation, the results suggest that the retaliations by the EU and Mexico appear more distinctly targeted.

For the EU retaliation exposure, individuals living in counties with the highest retaliation exposure would be characterised by a 31.5% higher propensity to express a favourable view of Trump as a candidate. For the Chinese retaliation, a county subject to an equivalent retaliation exposure is characterised by an 11.6% higher individual self-reported propensity to have a favourable view of Trump.

A potential concern with these findings is that the retaliation patterns may simply capture geographic differences of Republican versus Democratic support. To highlight that retaliatory tariffs do indeed appear to target areas with strong support for Donald Trump, we analyse the period in which the Republican nomination was still open and included Donald Trump as a candidate (July 2015 to March 2016).[13] We further focus on the subset of respondents who self-identify as Republican (≈23.4% of the sample). With this analysis we aim to capture whether retaliation exposure was distinctively targeted against areas who supported Trump instead of another Republican presidential candidate.

The results are presented in Table 3. Throughout Panels (a)–(d) the dependent variable is a dummy indicating whether a respondent expresses a favourable opinion of the Republican presidential candidate indicated in the panel label. The results indicate a clear pattern. The EU and Chinese retaliations specifically targeted part of the USA in which Trump was more popular among self-identifying Republicans. In contrast, no such relationship exists when we consider the support for any of the other presidential candidates. For the Mexican and the Canadian retaliation, the correlation is also positive but statistically insignificant. This finding suggests that retaliation was carefully chosen to target areas with Republican supporters with an affinity for Donald Trump. The specific targeting of Trump's voter base exhibits parallels to the targeting of politically connected firms for economic sanctions in Iran (Draca *et al.*, 2018), both of which are likely to increase the pressure on the respective political leaders.

Last, in Figure 3 we present the estimated difference-in-difference coefficients from specification (3). The figure suggests that the correlation between a county's exposure to retaliation and indviduals' leaning towards the Republican Party becomes distinctly stronger from 2016 onwards. This suggests that retaliation was targeted against areas that increased their support for the Republican Party relative to the 2015 baseline level. In other words, areas that have been swayed to support Republicans during Trump's presidential run were more strongly targeted than areas that have always exhibited a strong support of the Republican Party. It is also worth noting that trends prior to 2015 are flat. This suggests that our retaliation measure is not confounding other latent trends in the geography of Republican Party affiliation that pre-date Donald Trump's candidacy.[14] If we were simply picking up the trade-induced manufacturing sector decline (Autor *et al.*, 2016), for example, this trend should be visible before the 2016 presidential election.

We next explore a short individual-level panel highlighting that retaliation, especially from the EU and China, is targeted against areas of the USA that saw sizeable swings from supporting Obama in 2012 to supporting Trump in 2016.

[13] Donald Trump announced his candidacy formally on 16 June 2015 and became the presumptive nominee on 4 May 2016. We focus on the period between his announcement and March 2016 in order to have a consistent sample for comparisons across the four main Republican candidates—Marco Rubio, Ted Cruz, John Kasich and Donald Trump—who survived the race up until March. From March 2016 onwards Marco Rubio dropped out of the race and it appeared increasingly unlikely that Trump would be denied the nomination.

[14] For example, the growth of partisan media (DellaVigna and Kaplan, 2007; Levendusky, 2013), gerrymandering (McCarty *et al.*, 2009), intra-party political movements (Williamson *et al.*, 2011; Madestam *et al.*, 2013) and geographic polarisation (Martin and Webster, 2020).

Table 3. *Measuring Degree of Political Targeting: Exploiting Individual Level within 2016 Republican Party Presidential Candidate Variation from June 2015 to March 2016.*

	(1)	(2)	(3)	(4)	(5)
		Retaliatory tariffs imposed by ...			
DV: Favourable view of ...	Combined	CN	EU	CA	MX
Panel (a): Donald Trump					
Retaliation exposure	0.658***	0.670***	3.559**	0.693	3.565
	(0.177)	(0.203)	(1.405)	(0.864)	(2.220)
Observations	12,806	12,806	12,806	12,806	12,806
Counties	2,035	2,035	2,035	2,035	2,035
Mean of DV	0.591	0.591	0.591	0.591	0.591
Panel (b): Ted Cruz					
Retaliation exposure	0.199	0.174	0.575	0.897*	1.352
	(0.151)	(0.187)	(1.373)	(0.497)	(1.335)
Observations	12,998	12,998	12,998	12,998	12,998
Counties	2,051	2,051	2,051	2,051	2,051
Mean of DV	0.569	0.569	0.569	0.569	0.569
Panel (c): Marco Rubio					
Retaliation exposure	−0.537***	−0.659***	−0.234	0.088	−1.771
	(0.188)	(0.216)	(1.429)	(0.781)	(2.527)
Observations	11,554	11,554	11,554	11,554	11,554
Counties	2,023	2,023	2,023	2,023	2,023
Mean of DV	0.588	0.588	0.588	0.588	0.588
Panel (d): John Kasich					
Retaliation exposure	−0.650***	−0.860***	−1.835	0.135	−1.086
	(0.153)	(0.164)	(1.187)	(0.583)	(1.852)
Observations	13,071	13,071	13,071	13,071	13,071
Counties	2,050	2,050	2,050	2,050	2,050
Mean of DV	0.376	0.376	0.376	0.376	0.376
Sample			Self-identifying Republicans		
State FE	Yes	Yes	Yes	Yes	Yes
Race	Yes	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes
Gender	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is an indicator stating whether a respondent holds a favourable view of the candidate indicated. The responses include 'don't know', 'refused' and 'no view'. The patterns are robust to dropping these observations. Regressions include individual-level controls: the respondent's racial identity, income, Republican Party affiliation and gender, and the year of the survey. Regressions are weighted using survey weights provided by Gallup. Standard errors are clustered at the county level and are presented in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

2.4. *Individual-Level Panel Data*

As an additional piece of evidence, we leverage the 2016 CCES study, which asked respondents if and for whom individuals voted in the 2012 and 2016 presidential elections. The advantage of the CCES in comparison to the Gallup data is that it directly measures voting behaviour instead of approval or party affiliation. In this way, the CCES data allow us to study whether individuals switched their party support vis-à-vis the 2012 election. We estimate regression specification (2). The set of individual-level controls X_i includes race, gender, age, income and political party affiliation. As we estimate the regression in first differences, we implicitly account for time-invariant individual-level characteristics (similar to individual fixed effects). In particular, we study the direction of the switch—i.e., whether retaliation was concentrated in counties with

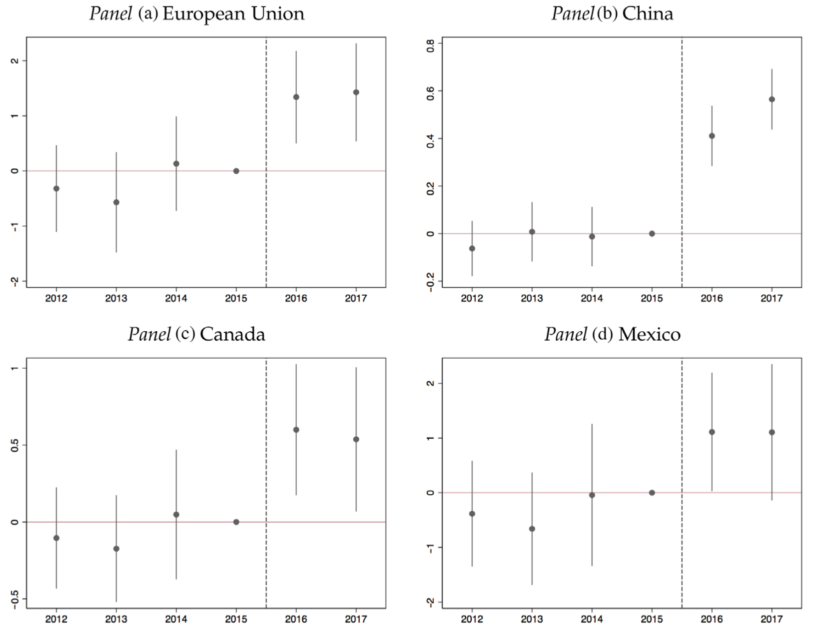

Fig. 3. *Was Retaliation Targeted? Evidence from Individual-Level Republican Party Affiliation and County-Level Exposure to Retaliatory Tariffs.*

Notes: The figure plots regression results capturing how the strength of the correlation between individual-level Republican Party affiliation and the county-level retaliation exposure measure evolved over time across the Gallup samples. Throughout, it appears that the correlation becomes markedly stronger from 2016, suggesting that retaliation was targeted towards areas with resident respondents who identify with the Republican Party under Donald Trump from 2016 onwards. The omitted year is 2015. All regressions control for county fixed effects and year effects, as well as indicators for race, gender and income across 12 categories. Confidence intervals of 90% obtained from clustering standard errors at the county level are indicated. Observations are weighted using the provided survey weights.

voters that swung from supporting Barack Obama to supporting Donald Trump. The results from this analysis are presented in Online Appendix Table A10.

The patterns are very similar and consistent with the previous results on the county level and from the Gallup daily tracker. In Panel (a) we focus on self-reported voting for Donald Trump in 2016, while controlling for Republican Party affiliation. Magnitudes of the point estimates suggest that in counties most exposed to EU retaliation, voters' propensity to support Donald Trump in 2016 was 62% higher.

We also explore the targeting properties studying voter moves between candidates in 2012 and 2016 in Panels (b) and (c). The point estimates suggest that the retaliation appears to target counties with more swing voters. Specifically, in Panel (c), we focus on voters who swung from supporting Barack Obama in 2012 to supporting Donald Trump in 2016, with results suggesting that retaliation was mainly targeted to hit counties that saw voters switch from Obama to Trump.

The estimates are statistically significant for the EU and Chinese retaliation exposure measures. The point estimates suggest that in counties most targeted by EU retaliation, the likelihood of an individual voter to be a swing voter that switched from supporting Obama to Trump is 7.6%

higher. For counties exposed to Chinese retaliation at the same level, the likelihood is 3.8% higher.[15]

Taken together, the results suggest that retaliation appears to have been chosen to target counties in which Trump had a particular appeal and voters increased their support for the Republican Party. The patterns documented across three different data sources are remarkably consistent. Additionally, the fact that the Trump administration provided billions of dollars in farm aid packages (see, for example, Davis and Swanson, 2018) suggests that the effect of retaliatory tariffs was felt in the targeted areas. In Section 2 of the Online Appendix we provide auxiliary evidence for the economic consequences of the tariffs. In line with the findings of Levitt and Snyder (1995) and Berry *et al.* (2010) on pork barrel spending, the farm aids can be interpreted as an attempt to mitigate the political fallout from the trade war.

A remaining concern is that the underlying patterns could be spurious in a fashion that can not be accounted for with individual-level or other county-level control variables. Specifically, one might worry that the specific mix of products that countries purchase from the USA may mechanically constrain the structure of *any* retaliation response. To address this concern, we exploit the fact that for the initial wave of tariffs—which we study in this paper—the constraints on the retaliation response are quite well defined. This allows us to construct counterfactual baskets that countries could have chosen and evaluate the degree of political targeting against these counterfactuals. These counterfactual baskets additionally allow us to investigate other constraints on the retaliation response.

3. Counterfactual Retaliation Baskets

Is the observed targeting of Republican counties a mere artefact of the US export mix with specific trading partners, and do trading-partners face trade-offs due to domestic constraints? In this section we attempt to answer these questions by proposing a simulation approach exploiting retaliation design constraints to construct feasible counterfactual retaliation baskets.

3.1. *Retaliation Design Constraints*

In our simulations we leverage the fact that trading rules impose constraints on the design of retaliation (or, more formally, rebalancing measures). The key constraint is that the applied retaliatory tariffs should be commensurate with the US tariffs. For example, the tariffs imposed by the USA on steel and aluminium affected around \$7.2 billion of EU exports to the USA, with an expected added overall tariff revenue volume of \$1.6 billion.[16] To comply with WTO rules, the EU's expected tariff revenues from the retaliation should not exceed this amount.

Our aim therefore is to identify a vector of products i among all traded HS goods categories for which there are non-zero imports, $M_{i,r} > 0$, into retaliating country r along with a vector of non-zero tariff rates $t_{i,r} > 0$ to be applied such that the combined expected tariff revenues $\sum_{i \in \mathcal{S}_r} t_{i,r} M_{i,r}$ are less than the expected tariff revenues that the USA levies on imports from country r, T_r. As previously discussed, the choice of tariff rates is secondary for the retaliation wave we are studying: for 85% of product classes included in the actual retaliation, the added tariff rate was fixed at 25%. For the counterfactual construction, therefore, we ignore the choice

[15] In Online Appendix Table A11 we confirm the results for the subset of voters whose voting status has been validated based on official voter lists. The patterns remain broadly the same, even though we do lose some statistical precision.

[16] See https://europa.eu/rapid/press-release_IP-18-4220_en.htm (last accessed: 31 October 2020).

of the added tariff rate $t_{i,r}$, implicitly assuming a fixed rate t.[17] With a fixed tariff rate the above problem becomes a *subset sum* problem.

Nevertheless, even this subset sum problem is computationally difficult to solve. A subset sum problem is NP-complete, meaning that the most efficient algorithm for finding a solution has a running time of order $O(2^{\frac{N}{2}})$, where N is the number of elements in the set. In our case the exponential growth of the running time combined with the large number of potential HS product codes to choose from makes it computationally infeasible to derive the complete set of possible retaliatory baskets. To illustrate: at the eight-digit HS code level, there are around 4,000 goods for which US imports to the EU exceeded \$1 million in 2017; furthermore, there are around 400 goods for which imports exceeded \$100 million in 2017 (see Online Appendix Figure A4). This potentially leaves an uncountably large set of combinations of products for which the combined affected imports from the USA is approximately equal to the US tariffs. To overcome this challenge, we use a probabilistic simulation approach to identify a set of alternative baskets.

3.2. *Simulation Approach*

In particular, we use the following sampling procedure for each country's retaliation list L:

while *fewer than 1,000 alternative retaliation baskets* $\mathcal{L}_{r,i}$ *have been found:* **do**

1. Randomly draw an integer N_i indicating length of retaliation list in terms of HS10 codes—allow for a 20% deviation around list length of actual retaliation N_{r*}

2. Draw a sample list $\mathcal{L}_{i,r}$ of HS10 codes of length N_i on which there is some exports from the US in 2017

3. Compute the volume of exports from USA to country r that would be affected by retaliation if the sample list $\mathcal{L}_{i,r}$ were chosen $\sum_{i\in\mathcal{L}_{i,r}} E_{i,US,r}$

4. **if** $0.9 < \frac{\sum_{i\in\mathcal{L}_{i,r}} E_{i,US,r}}{\sum_{i\in\mathcal{L}_r^*} E_{i,US,r}} < 1.1$ **then**

  Accept the candidate list $\mathcal{L}_{i,r}$;

  end

end

As indicated in the pseudo-code, we construct a counterfactual retaliation list by first choosing a similar number of products to target (allowing for a 20% deviation). We then sample a set of products to target and calculate the effected export volume. Last, we accept any list that affects a similar amount of exports as the actual list (allowing for a 10% deviation). The result of our sampling procedure is a set of retaliation lists that are similar to the original list in many dimensions but target a different set of US exports. While the simulation approach traces out some aspects of the 'retaliation possibilities frontier', it ignores two potential strategic elements. First, retaliation lists may be designed in a way that preserves an option value to hit back in case of a further escalation. Second, retaliating countries may coordinate their retaliation responses to maximise their effectiveness. It is also important to note that the counterfactual retaliation bundles are not orthogonal to the actual retaliation basket (see Online Appendix Figure A5). The

[17] In Online Appendix Figure A2 we highlight that the implied county-level retaliation exposure measure accounting for the actual tariff rate vis-à-vis the measure that ignores the rate are statistically virtually identical.

Table 4. *Evaluation of Actual Retaliation Response Relative to Counterfactual Retaliation: Evaluating Political Targeting.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	County level		Gallup capturing Trump			CCES Trump	
	GOP_{2016}	ΔGOP_{2012}^{2016}	Favourable view	Approval	Vote	Switched to	Obama to Trump
$\Pr(\hat{\beta}_{i,r} > \hat{\beta}_{r^*})$							
CN	0.221	0.131	0.060	0.070	0.052	0.060	0.060
EU	0.351	0.203	0.240	0.280	0.220	0.188	0.212
CA	0.940	0.811	0.650	0.760	0.780	0.800	0.768
MX	0.257	0.172	0.520	0.580	0.512	0.552	0.476

Notes: The table reports analysis of the implied measures of the extent of political targeting implied by the set of simulated counterfactual retaliation baskets vis-à-vis the actually chosen retaliation response. The figures represent the share of retaliation baskets that imply a retaliation exposure measure above what is implied in the actually chosen retaliation response. Columns (1)–(2) study the county-level data explored in Table 1, columns (3)–(5) use the measures leveraged in Table 2, while columns (6)–(7) explore the measures studied in Online Appendix Table A10.

observed positive correlation mechanically results because the simulated baskets overlap with the actual retaliation basket.

3.3. *Evaluating the Degree of Political Targeting*

The simulation approach is particularly useful as it allows us to *quantify* the degree of political targeting relative to the counterfactual baskets. More specifically, we evaluate whether retaliation appears at the upper or lower end of the potential retaliation distribution. We also investigate the underlying trade-offs that countries face in their retaliation design. For this analysis we estimate the regression models studied in Tables 1 and 2 and Online Appendix Table A10 for counterfactual retaliation lists and the implied counterfactual county-level retaliation exposure measures.[18] The result of this exercise is a vector of estimates $\hat{\boldsymbol{\beta}}_r = (\hat{\beta}_r^1, \ldots., \hat{\beta}_r^{1,000})$ measuring the correlations between the simulated counterfactual tariff exposure measures and the outcome of interest (e.g., Republican vote share). We compare this vector of estimates relative to the estimate $\hat{\beta}_r^*$ for the actual retaliation list $\mathcal{L}_r$.

Table 4 presents the share of the counterfactual estimates $\hat{\boldsymbol{\beta}}_r$ that would imply a higher level of political targeting. In columns (1) and (2) we focus on the outcomes studied in Table 1. Column (1) suggests that for China, there exist hardly any feasible and comparable retaliation responses that would produce a stronger (conditional) correlation with the 2016 Republican vote share. For the EU, around 29% of bundles would have a higher degree of political targeting. For Canada and Mexico, these numbers are 73.4% and 51.2%, respectively. This suggests that retaliation by these countries could have been designed in a fashion that would have achieved a higher degree of targeting at this particular moment. In column (2) we study the changes in the Republican vote share from 2012 to 2016. The EU's and China's retaliation responses again appear more targeted than most counterfactual baskets. For Canada and Mexico, the measures are in the middle of the counterfactual distribution. This again suggests that retaliation could have been chosen to produce a higher degree of political targeting. In columns (3)–(7) we study the other outcome

[18] Note that there is a non-negligible cross-correlation across retaliation bundles. Online Appendix Figure A5 highlights that the implied measures and the actually chosen retaliation response have a positive correlation across almost all of the 1,000 counterfactual bundles. This is merely a direct result of the fact that the retaliation response that meets the criteria to be quite similar will produce some overlap, implying a mechanical cross-correlation.

measures explored in Table 2 and Online Appendix Table A10. The observed patterns are broadly similar.

The finding that Canadian and Mexican retaliation, while being quite robustly associated with support for Donald Trump, does not appear to be at the upper end of the achievable targeting distribution suggests that other considerations may have played just as important a role. We next aim to investigate which other objectives countries might include in their considerations.

3.4. *Retaliation Trade-Offs*

The previous section suggests that retaliation appears to specifically target parts of the USA that swung to support Donald Trump. Yet, relative to a set of counterfactual retaliation responses, especially for Canada and Mexico, we observed that the implemented choice seems suboptimal. What might explain this observation? As our discussion of the EU's retaliation design objectives suggested, countries designing their retaliation have multiple objectives. In the EU regulation constraining retaliation design, the mitigation of harm to consumers and firms features prominently along with political effectiveness. In this section we construct a set of relevant measures that might constrain the retaliation choice. In particular, we investigate the role of revealed comparative advantage, import demand elasticities and the dominance of US exports.

Revealed comparative advantage: The first measure is an index of the revealed comparative advantage (RCA), as introduced by Balassa (1965). The intuition for this index, which is constructed based on export data, is that a country appears to have a revealed comparative advantage for a good h if a higher share of the country's export is accounted for by this good relative to the export share of this good across all trading countries. Formally, an RCA value above 1 for a specific good h indicates that a country has a revealed comparative advantage (see Kavaklí *et al.*, 2020 for a recent example using RCA measures in the context of economic sanctions). When designing their retaliation responses, countries might reasonably want to avoid goods for which the USA has a revealed comparative advantage. We denote the implied average RCA for each retaliation list as $RCA_{i,r}$, which we weight by the implied volume of trade.[19] As the construction of the RCA indices requires trade data between all countries, we can construct the RCA only at the HS six-digit level, based on data from UN Comtrade.

Import demand elasticities: Whether a specific good is chosen for retaliation may also depend on the associated (import) demand elasticities. Presumably, in order for retaliation to be effective, goods for which import demand is found to be particularly price-elastic would prove to be more effective. Furthermore, tariffs on goods with a high import demand elasticity are less likely to affect domestic consumers. We therefore use the import demand elasticity estimates constructed by Soderbery (2018) at the HS4 level for each of the retaliating countries. As before, we compute the retaliation-specific weighted average import demand elasticity specific to a counterfactual retaliation list i for country r, $\sigma_{i,r}$ and evaluate this against the elasticities associated with the actually chosen retaliation response, σ_{r^*}.[20]

Dominance of US exports: Countries might also want to avoid retaliating and raising the cost of specific imports for which the USA is the predominant source. To measure this, we construct the share of imports $I_{i,h,r}$ of a good h on a retaliation list i of country r that stems from the

[19] While the sum of the weights across baskets will be the same as our counterfactual baskets targeting a similar volume of trade, the distribution of weights will differ.

[20] For the EU, we use estimated elasticities for Germany—as the USA's biggest trading partner—from Soderbery (2018). The results are qualitatively similar if we use other EU countries as a reference.

Table 5. *Summary Statistics of Counterfactual Retaliation Baskets vis-à-vis Actual Retaliation Response.*

	Retaliatory tariffs imposed by . . .							
	CN		EU		CA		MX	
	Mean (SD)	Actual r^*	Mean (SD)	Actual r^*	Mean (SD)	Actual r^*	Mean (SD)	Actual r^*
$RCA_{i,r}$	2.101 0.484	3.296	1.788 0.335	1.511	1.373 0.260	0.990	1.524 0.441	1.301
Import demand elasticity $\sigma_{i,r}$	3.845 0.346	4.384	3.178 0.179	3.070	3.834 0.387	3.886	3.115 0.836	3.348
US import market share $s_{i,r}$	0.226 0.042	0.369	0.158 0.071	0.132	0.668 0.041	0.760	0.690 0.121	0.723

Notes: The table presents summary statistics of the other measures constructed for the counterfactual retaliation baskets along with the measure for the actually implemented retaliation basket.

Table 6. *Retaliation Design Trade-Offs.*

	(1) CN	(2) EU	(3) CA	(4) MX
Share of retaliation bundles with . . .				
$\Pr(RCA_{i,r} < RCA_{r^*})$	0.982	0.198	0.036	0.331
Import demand elasticity $\Pr(\sigma_{i,r} > \sigma_{r^*})$	0.059	0.686	0.599	0.073
US import market share $\Pr(s_{i,r} < s_{r^*})$	1.000	0.459	0.996	0.564

Notes: The table evaluates the further measures associated with counterfactual retaliation responses against the measure associated with the actual retaliation chosen. The figures compute the share of counterfactual baskets above or below the value associated with the actual retaliation response.

USA relative to the rest of the world, $s_{h,i,r} = \frac{I_{i,h,r}}{\sum_c I_{h,c}}$. We compute the trade volume–weighted average implied share of US imports, $s_{i,r}$ for each good in the retaliation lists, across each of the counterfactual retaliation lists i for country r. We then again evaluate the corresponding shares associated with the actual retaliation list s_{r^*} compared to the counterfactual lists. This analysis is conducted at the HS6 level (based on UN Comtrade data).

In Table 5 we report summary statistics for the three measures and how they compare across retaliation baskets. Ideally, in order to minimise harm to their own economies, countries would favour retaliating against goods with a low RCA, a large import demand elasticity and a low US import market share. In Table 6 we contrast how the distribution of counterfactual baskets compares with the actual retaliation response. The EU's retaliation appears to be targeting goods for which the USA has a weaker RCA and goods of which the USA is a less dominant supplier. The Mexican response, on the other hand, appears to target goods with a relatively high import demand elasticity and a lower revealed comparative advantage.

We next shed light on the underlying trade-offs visually.

Results: For every (potential) retaliation list i of retaliating country r, we have now constructed a vector of attributes $(\hat{\beta}_{i,r},\ RCA_{i,r},\ s_{i,r},\ \sigma_{i,r})$. To illustrate the trade-offs and constraints imposed on retaliation design, we visualise the joint distribution of the pair $(\hat{\beta}_{i,r},\ RCA_{i,r})$ in Figure 4. The horizontal axis measures the degree of political targeting (measured by the changes in the Republican Party vote share between 2012 and 2016). The vertical axis captures the different RCA index values. Conceptually, countries should aim to design retaliation in the bottom right

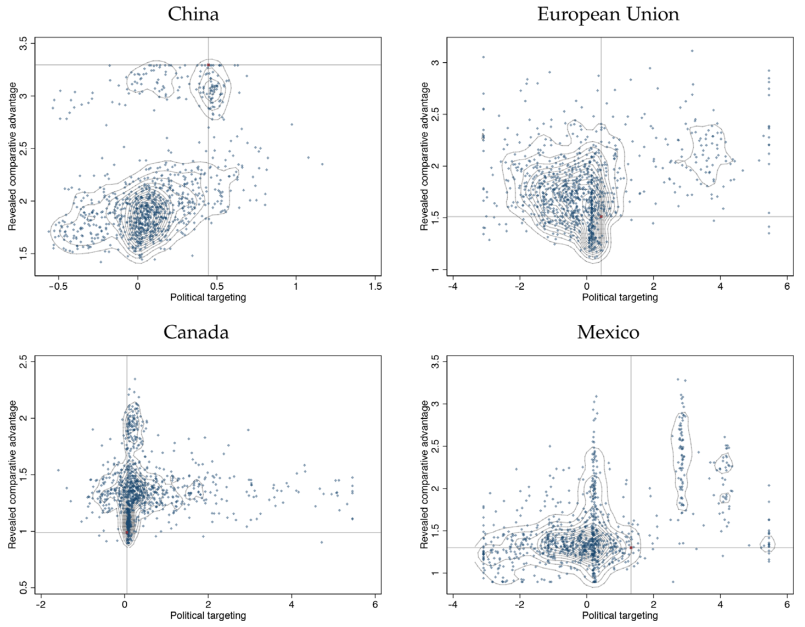

Fig. 4. *Trade-Off in Political Targeting and Revealed Comparative Advantage of USA: ΔGOP Vote Share, 2012–2016.*

Notes: The figure plots bivariate kernel densities of the joint distribution the two measures across the 1,000 simulated retaliation baskets. The vertical axis presents the revealed comparative advantage index, while the horizontal axis displays the degree of political targeting. Areas in the lower right corner indicate high degrees of political targeting of a specific retaliation basket and lower revealed comparative advantage. The implied values for the actual baskets are indicated as horizontal and vertical lines.

corner, as this would imply a high degree of political targeting, while at the same time targeting goods with a low revealed comparative advantage.

The figure also highlights some of the specifics around the feasible counterfactual retaliation set. For China, there are very limited choices available for designing a commensurate retaliation response (top right corner). While there exists a broad set of *feasible* retaliation bundles, the vast majority of them would imply weak political targeting, even targeting counties that swung away from Trump. Among the few bundles with positive political targeting, the revealed comparative advantage measure for the USA is high. This shows that the structure of US exports to China, which is concentrated in agricultural produce and high-technology manufactured goods, places significant constraints on the Chinese ability to retaliate.[21] For the EU, Canada and Mexico, which share a much more diverse goods-trade relationship with the USA, there are far fewer constraints on retaliation design. Relative to the counterfactual baskets, we observe that for the EU and China in particular, retaliation appears to have been chosen at the upper end. To the best of our knowledge, we are not aware of another paper that has explored retaliation in this way. For the EU, there exist very few alternative retaliation bundles that would produce a higher degree

[21] See Costa *et al.* (2016) for work on the impact of China's commodities-for-manufactures trade and Garred (2018) for China's trade policy post–WTO accession.

Table 7. *Trade-Offs and Targeting in Retaliation Design: Evidence from Counterfactual Retaliation Responses.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	County level		Gallup capturing Trump		CCES Trump		
	GOP_{2016}	ΔGOP_{2012}^{2016}	Favourable view	Approval	Vote	Switched to	Obama to Trump
Panel (a): $\Pr(\hat{\beta}_{i,r} > \hat{\beta}_{r^*})$							
CN	0.221	0.131	0.060	0.070	0.052	0.060	0.060
EU	0.351	0.203	0.240	0.280	0.220	0.188	0.212
CA	0.940	0.811	0.650	0.760	0.780	0.800	0.768
MX	0.257	0.172	0.520	0.580	0.512	0.552	0.476
Panel (b): $\Pr(\hat{\beta}_{i,r} > \hat{\beta}_{r^*} \cap RCA_{i,r} < RCA_{r^*})$							
CN	0.206	0.122	0.050	0.060	0.044	0.052	0.052
EU	0.043	0.008	0.010	0.010	0.016	0.008	0.012
CA	0.035	0.033	0.010	0.020	0.020	0.032	0.036
MX	0.052	0.014	0.160	0.180	0.132	0.164	0.120
Panel (c): $\Pr(\hat{\beta}_{i,r} > \hat{\beta}_{r^*} \cap \sigma_{i,r} > \sigma_{r^*})$							
CN	0.020	0.013	0.020	0.020	0.016	0.016	0.016
EU	0.254	0.147	0.170	0.210	0.148	0.128	0.148
CA	0.570	0.494	0.420	0.500	0.456	0.460	0.440
MX	0.010	0.011	0.010	0.010	0.012	0.012	0.008
Panel (d): $\Pr(\hat{\beta}_{i,r} > \hat{\beta}_{r^*} \cap s_{i,r} < s_{r^*})$							
CN	0.221	0.131	0.060	0.070	0.052	0.060	0.060
EU	0.139	0.070	0.110	0.130	0.084	0.076	0.088
CA	0.936	0.807	0.650	0.760	0.780	0.800	0.768
MX	0.119	0.062	0.280	0.340	0.268	0.244	0.172

Notes: The table reports an analysis of the implied measures of the extent of political targeting implied by the set of simulated counterfactual retaliation baskets vis-à-vis the actually chosen retaliation responses. The figures represent the share of retaliation baskets that imply a retaliation exposure measure above what is implied in the actually chosen retaliation responses. Columns (1)–(2) study the county-level data explored in Table 1, columns (3)–(5) use the measures leveraged in Table 2, while columns (6)–(7) explore the measures studied in Online Appendix Table A10.

of political targeting and a lower RCA value. The same is true for Canada, and to a lesser extent for Mexico.

In Online Appendix Figure A6 we study the implied import demand elasticity. The figure highlights that, for both Canada and Mexico, retaliation appears to be targeted towards goods with a high import demand elasticity and a higher degree of political targeting. Online Appendix Figure A7 studies the implied US market power for specific retaliation baskets. Based on this measure, the EU's retaliation response stands out as achieving a fair degree of political targeting, while avoiding goods of which the USA is a dominant supplier.

In Table 7 we compute the shares of retaliation baskets that would imply a higher degree of political targeting while considering our other proxies capturing retaliation effectiveness and domestic economic harm. Throughout, the chosen retaliation appears at the upper end in terms of producing high political targeting but a lower RCA. For the EU, only around 1% of the counterfactual retaliation responses would produce a higher degree of political targeting and a lower RCA. The Chinese retaliation response clearly stands out, as it appears to target goods with a high RCA. Much of this is afforded by the specific constraints that Chinese retaliation design faces, as the vast majority of other feasible retaliation baskets would produce no political targeting whatsoever.

4. Conclusion

Based on the recent trade escalation provoked by the administration of Donald Trump, this paper provides empirical evidence for the political targeting of retaliatory tariffs. Using a novel simulation approach, we show that retaliatory tariffs have indeed disproportionately targeted more Republican areas. This suggests that retaliatory tariffs appear to have a clear political dimension. We further illustrate that countries face a trade-off between the degree of political targeting and the potential harm done to their own economies. Our findings suggest that countries appear to place different emphases on these two policy objectives. To the best of our knowledge, this paper is the first to empirically document this trade-off.

Future work should therefore investigate whether retaliation is effective in shaping the underlying trade policy preferences of politicians and the electorate more broadly. This paper suggests that such an empirical study—for example, using difference-in-difference designs—will have to find a way to navigate the endogeneity of retaliation exposure that this paper highlights.

University of Warwick, CEPR, CESifo & CAGE, UK
Bocconi University & CAGE, Italy

Additional Supporting Information may be found in the online version of this article:

Online Appendix
Replication Package

References

Ahn, D.P. and Ludema, R.D. (2017). *Measuring Smartness: Understanding the Economic Impact of Targeted Sanctions*, Washington, DC: US Department of State.
Alesina, A. and Rosenthal, H. (1995). *Partisan Politics, Divided Government and the Economy*, New York: Cambridge University Press.
Alesina, A. and Rosenthal, H. (2006). 'A theory of divided government', *Econometrica*, vol. 64(6), p. 1311.
Allen, S.H. (2008). 'The domestic political costs of economic sanctions', *Journal of Conflict Resolution*, vol. 52(6), pp. 916–44.
Amiti, M., Redding, S. and Weinstein, D. (2019). 'The impact of the 2018 trade war on U.S. prices and welfare', Working Paper, National Bureau of Economic Research.
Ansolabehere, S. and Rivers, D. (2013). 'Cooperative survey research', *Annual Review of Political Science*, vol. 16(1), pp. 307–29.
Autor, D., Dorn, D., Hanson, G. and Majlesi, K. (2016). 'Importing political polarization? The electoral consequences of rising trade exposure', Discussion Paper 11511, Centre for Economic Policy Research.
Autor, D.H., Dorn, D. and Hanson, G.H. (2013). 'The China syndrome: local labor market impacts of import competition in the United States', *American Economic Review*, vol. 103(6), pp. 2121–68.
Baccini, L. (2010). 'Explaining formation and design of EU trade agreements: the role of transparency and flexibility', *European Union Politics*, vol. 11(2), pp. 195–217.
Baker, A. (2005). 'Who wants to globalize? Consumer tastes and labor markets in a theory of trade policy beliefs', *American Journal of Political Science*, vol. 49(4), pp. 924–38.
Balassa, B. (1965). 'Trade liberalisation and "revealed" comparative advantage', *The Manchester School*, vol. 33(2), pp. 99–123.
Baldwin, R.E. (2004). 'Openness and growth: what's the empirical relationship?', in (R.E. Baldwin and L.A. Winters, eds.), *Challenges to Globalization: Analyzing the Economics*, Chicago: University of Chicago Press.
Barari, S., Kim, I.S. and Wong, W. (2019). 'Trade liberalization and regime type: evidence from a new tariff-line dataset', Massachusetts Institute of Technology, Working Paper.
Berry, C.R., Burden, B.C. and Howell, W.G. (2010). 'The President and the distribution of federal spending', *American Political Science Review*, vol. 104(4), pp. 783–99.
Bown, C.P. (2004). 'On the economic success of Gatt/WTO dispute settlement', *Review of Economics and Statistics*, vol. 86(3), pp. 811–23.

Breuss, F. (2004). 'WTO dispute settlement: an economic analysis of four EU–US mini trade wars', *Journal of Industry, Competition and Trade*, vol. 4(4), pp. 275–315.
Brookings. (2017). 'Export Monitor', Technical Report.
Cameron, G.T. and Schuyler, P. (2007). 'The political economy of international agricultural protection', *Journal of Politics*, vol. 69(1), pp. 116–27.
Chan, S.P. and Smale, W. (2018). 'Hit them in the Harleys: EU fights Trump tariffs', https://www.bbc.co.uk/news/business-43926092 (last accessed: 28 October 2020).
Che, Y., Lu, Y., Pierce, J.R., Schott, P.K. and Tao, Z. (2017). 'Did trade liberalization with China influence U.S. elections?', National Bureau of Economic Research, Working Paper.
Colantone, I. and Stanig, P. (2018a). 'Global competition and Brexit', *American Political Science Review*, vol. 112(2), pp. 201–18.
Colantone, I. and Stanig, P. (2018b). 'The trade origins of economic nationalism: import competition and voting behavior in Western Europe', *American Journal of Political Science*, vol. 62(4), pp. 936–53.
Costa, F., Garred, J. and Pessoa, J.P. (2016). 'Winners and losers from a commodities-for-manufactures trade boom', *Journal of International Economics*, vol. 102, pp. 50–69.
Davis, J.H. and Swanson, A. (2018). 'To ease pain of Trump's trade war: $12 billion in aid for farmers', https://www.nytimes.com/2018/07/24/us/politics/farmers-aid-trade-war.html (last accessed: 28 October 2020).
DellaVigna, S. and Kaplan, E. (2007). 'The Fox News effect: media bias and voting', *Quarterly Journal of Economics*, vol. 122(3), pp. 1187–234.
Dippel, C., Gold, R. and Heblich, S. (2015). 'Globalization and its (dis-)content: trade shocks and voting behavior', Working Paper 21812, National Bureau of Economic Research.
Draca, M., Garred, J., Stickland, L. and Warrinnier, N. (2018). 'On target? The incidence of sanctions across listed firms in Iran', Working Paper 372, Competitive Advantage in the Global Economy.
Eaton, J. and Engers, M. (1992). 'Sanctions', *Journal of Political Economy*, vol. 100(5), pp. 899–928.
Elliott, K.A. and Hufbauer, G.C. (1999). 'Same song, same refrain? Economic sanctions in the 1990's', *American Economic Review*, vol. 89(2), pp. 403–8.
Enamorado, T. and Imai, K. (2018). *Validating Self-Reported Turnout by Linking Public Opinion Surveys with Administrative Records*, Political Behavior: Cognition.
Fajgelbaum, P.D., Goldberg, P.K., Kennedy, P.J. and Khandelwal, A.K. (2020). 'The return to protectionism', *Quarterly Journal of Economics*, vol. 135(1), pp. 1–55.
Feigenbaum, J.J. and Hall, A.B. (2015). 'How legislators respond to localized economic shocks: evidence from Chinese import competition', *Journal of Politics*, vol. 77(4), pp. 1012–30.
Frankel, J.A. and Romer, D.H. (1999). 'Does trade cause growth?', *American Economic Review*, vol. 89(3), pp. 379–99.
Garred, J. (2018). 'The persistence of trade policy in China after WTO accession', *Journal of International Economics*, vol. 114, pp. 130–42.
Gawande, K. and Hansen, W.L. (1999). 'Retaliation, bargaining, and the pursuit of "free and fair" trade', *International Organization*, vol. 53(1), pp. 117–59.
Grossman, G.M. and Helpman, E. (1994). 'Protection for sale', *American Economic Review*, vol. 84(4), pp. 833–50.
Guiso, L., Herrera, H., Morelli, M. and Sonno, T. (2018). 'Populism: demand and supply', Working Paper, Centre for Economic Policy Research.
Hansen, J.M. (1990). 'Taxation and the political economy of the tariff', *International Organization*, vol. 44(4), pp. 527–51.
Hecksher, E. and Ohlin, B. (1933). *Interregional and International Trade*, Cambridge, MA: Harvard University Press.
Irwin, D.A. (1998). 'The Smoot-Hawley tariff: a quantitative assessment', *Review of Economics and Statistics*, vol. 80(2), pp. 326–34.
Kavaklí, K.C., Chatagnier, J.T. and Hatipoglu, E. (2020). 'The power to hurt and the effectiveness of international sanctions', *Journal of Politics*, vol. 82(3), pp. 897–94.
Kono, D.Y. (2006). 'Optimal obfuscation: democracy and trade policy transparency', *American Political Science Review*, vol. 100(3), pp. 369–84.
Kovak, B.K. (2013). 'Regional effects of trade reform: what is the correct measure of liberalization?', *American Economic Review*, vol. 103(5), pp. 1960–76.
Levendusky, M.S. (2013). 'Why do partisan media polarize viewers?', *American Journal of Political Science*, vol. 57(3), pp. 611–23.
Levitt, S.D. and Snyder, J.M. (1995). 'Political parties and the distribution of federal outlays', *American Journal of Political Science*, vol. 39(4), pp. 958–80.
Lü, X., Scheve, K. and Slaughter, M.J. (2012). 'Inequity aversion and the international distribution of trade protection', *American Journal of Political Science*, vol. 56(3), pp. 638–54.
Madestam, A., Shoag, D., Veuger, S. and Yanagizawa-Drott, D. (2013). 'Do political protests work? Evidence from the Tea Party movement', *Quarterly Journal of Economics*, vol. 128(4), pp. 1633–85.
Marinov, N. (2005). 'Do economic sanctions destabilize country leaders?', *American Journal of Political Science*, vol. 49(3), pp. 564–76.
Martin, G.J. and Webster, S.W. (2020). 'Does residential sorting explain geographic polarization?', *Political Science Research and Methods*, vol. 8(2), pp. 215–31.

McCarty, N., Poole, K.T. and Rosenthal, H. (2009). 'Does gerrymandering cause polarization?', *American Journal of Political Science*, vol. 53(3), pp. 666–80.

Ricardo, D. (1891). *Principles of Political Economy and Taxation*, London: G. Bell.

Rosendorff, B.P. (2005). 'Stability and rigidity: the dispute settlement procedure of the WTO's dispute settlement procedure', *American Political Science Review*, vol. 99(3), pp. 389–400.

Sattler, T., Spilker, G. and Bernauer, T. (2014). 'Does WTO dispute settlement enforce or inform?', *British Journal of Political Science*, vol. 44(4), pp. 877–902.

Scheve, K. and Tomz, M. (1999). 'Electoral surprise and the midterm loss in US congressional elections', *British Journal of Political Science*, vol. 29(3), pp. 507–21.

Scheve, K.F. and Slaughter, M.J. (2001). 'What determines individual trade-policy preferences?', *Journal of International Economics*, vol. 54(2), pp. 267–92.

Schott, P.K. (2008). 'The relative sophistication of Chinese exports', *Economic Policy*, vol. 23, pp. 5–49.

Soderbery, A. (2018). 'Trade elasticities, heterogeneity, and optimal tariffs', *Journal of International Economics*, vol. 114, pp. 44–62.

Stasavage, D. (2004). 'Open-door or closed-door? Transparency in domestic and international bargaining', *International Organization*, vol. 58(4), pp. 667–703.

Williamson, V., Skocpol, T. and Coggin, J. (2011). 'The Tea Party and the remaking of Republican conservatism', *Perspectives on Politics*, vol. 9(1), pp. 25–43.