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# Tariffs and politics: evidence from Trump's trade wars

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# Tariffs and politics: evidence from Trump's trade wars

## Abstract

Are retaliatory tariffs politically targeted and, if so, are they effective? Do countries designing a retaliation response face a trade-off between maximizing political targeting and mitigating domestic economic harm? We use the recent trade escalation between the US, China, the European Union (EU) and the North American Free Trade Agreement (NAFTA) countries to answer these questions. We find substantial evidence that retaliation was directly targeted to areas that swung to Donald Trump in 2016 (but not to other Republican candidates running for office in the same year). We further assess whether retaliation was optimally chosen using a novel simulation approach constructing counterfactual retaliation responses. For China and particularly, for Mexico and Canada, the chosen retaliation appears suboptimal: there exist alternative retaliation bundles that would have produced a higher degree of political targeting, while posing a lower risk to damage the own economy. We further present evidence that retaliation produces economic shocks: US exports on goods subject to retaliation declined by up to USD 15.28 billion in 2018 and export prices have dropped significantly. Lastly, we find some evidence suggesting that retaliation is effective: in areas exposed to retaliation Republican candidates fared worse in the 2018 Midterm elections, and similarly Presidential approval ratings, especially among Democrats, have declined.

JEL-Codes: F130, F140, F160, F550, D720.

Keywords: trade war, tariff, targeting, political economy, elections, populism.

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# 1 Introduction

Economist have long studied the political economy underlying trade disputes. 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](#), too name just a few), it is widely accepted that tariffs, while able to help certain individual industries, are not only harmful for trading partners but also constitute an act of self-harm ([Bown, 2004](#); [Breuss, 2004](#)). To offer an explanation why politicians nonetheless often favour tariffs, the work by [Grossman and Helpman \(1994, 1995\)](#) highlighted the influence of domestic politics and special interest groups on trade policy. In the same spirit, [Maggi and Rodriguez-Clare \(1998\)](#) argue that trade agreements could work as a commitment device for politicians against domestic interests. Later work by [Gould and Woodbridge \(1998\)](#) and [Ossa \(2014\)](#) model trade disputes as competition between nations.

Trade disputes are very common place – in fact, [WTO \(2018\)](#) lists 316 GATT disputes from 1948 to 1995 – yet, few disputes reach a stage of escalation in which threatened tariffs are actually imposed or retaliation measures are triggered. As a result, we know little about how escalating trade disputes are actually fought. A markable exception is the recent trade-escalation provoked by the US administration under President Donald Trump starting in March 2018. It thus provides a unique and recent case allowing the study of an ongoing trade dispute in a data rich environment. The 2016 presidential campaign already hinted at potential changes to US trade policy under a Trump administration.<sup>1</sup> Nonetheless, the announcement on March 1, 2018 that the US would impose a 25% tariff on steel and a 10% tariff on aluminium imports came as a surprise. Initially exempt, Canada, Mexico, and the EU became subject to the steel and aluminium tariffs from May 31, 2018. Additionally, the Trump administration set a tariff of 25% on 818 categories of goods imported from China worth \$50 billion on July 6. Following the announcement of steel and aluminium tariffs, President Donald Trump asserted in

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<sup>1</sup>See for example “Trump accuses China of ‘raping’ US with unfair trade policy”, 2. May 2016, <https://www.bbc.co.uk/news/election-us-2016-36185012>, accessed, 05.02.2019.

a tweet that “Trade wars are good, and easy to win.” Following negotiations with the US, some countries gained permanent exemptions from the steel tariffs (such as South Korea, Argentina, Australia and Brazil). Yet, the dispute involving China, the European Union (EU), Canada, Mexico, as well as Turkey and India escalated. As a result these countries reciprocated with tariffs of their own targeting imports from the US many of which started to take effect from July 2018 onwards.

This paper tackles three main questions. First, we assess the extent and dimensions of (political) targeting of retaliatory measures taken by countries or trading blocks affected by US measures. Given the limited evidence on actual trade-escalations, the recent example allows to study the potential trade-offs that countries or trade blocks may consider when designing a retaliation response. Second, we study whether retaliation measures affect patterns of trade and, importantly, whether they produce real economic shocks. Third, we analyze whether the retaliation measures have political consequences. Specifically, we study whether areas and voters more exposed to retaliation measures change their political preferences as expressed through actual votes cast in elections or by studying President Trump’s approval ratings.

In the first part of the paper, we document that retaliatory tariffs are indeed strongly and distinctly targeted towards areas that supported Trump in the 2016 election. To assess the degree of political targeting, we combine highly granular data on overall US exports with county level data. This essentially allows us to construct county-specific shocks similar to [Autor et al. \(2013\)](#). Using this measure, we show that retaliatory tariffs, through the choice of products, distinctly targeted areas that *swung to Donald Trump* in the 2016 presidential election (and not areas that swung behind other Republican candidate in the House or Senate elections). Our estimates suggest that areas in the top decile of exposure to retaliatory measures from China exhibited an up to 5 percentage point stronger swing to Trump relative to the performance of the 2012 Republican candidate. For the retaliatory measures from the EU, Canada and Mexico the corresponding estimates are 3.6, 2.9 and 2.8 percentage points respectively. It appears that the targeting is sharp

and distinctly designed to hit areas that saw disproportionate changes in support for Donald Trump as Republican candidate in the Presidential elections 2016, but not to areas that swung to Republican candidates in the House or Senate elections that also took place in 2016. This suggests a high degree of calibration of the retaliation response, which, in the case of the European Union is designed using a secret algorithm, which has been described as “the weapon of war” in this dispute.<sup>2</sup>

The choice of retaliation bundles is ultimately limited to sets of goods for which positive trade is recorded. To rule out that the degree of political targeting we measure is accidental and to assess the overall degree or strength of targeting we develop a novel simulation approach. For each country, we construct conceivable alternative sets of goods baskets against which retaliation could have been mounted. For each simulated basket, we construct the implied county level retaliation exposure measures and are thus able to evaluate the strength of political targeting implied by these counterfactual baskets relative to the actual chosen basket. Hence, this allows us to assess to what extent “better” or “more targeted” baskets could have been chosen. We observe that the degree of political targeting of the retaliation measures for Canada and Mexico in particular, and to a lesser degree for the EU, could have been much stronger. There is little room for improvement for Chinese retaliation, which is constrained by the structure of trade flows between the US and China.

We further study to what extent retaliating countries face a trade-off between higher degrees of political targeting and a larger impact on their own domestic economy. We construct a measure for the share of imports that are sourced from the US for respective goods and construct this measure for the same set of simulated bundles. This allows us to visualize the trade-offs involved between the degree of political targeting and the extent to which retaliation may harm ones’ own economy. We observe that the EU’s retaliation stands out in picking products for which the US is not a dominant supplier to the European market, thereby likely minimizing economic harm in the EU. For the other countries, the remarkable ob-

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<sup>2</sup>This quote is from a conversation that the authors had with an anonymous source in the EU Commission.

servation is that retaliation seems to put little emphasis on minimizing disruption to the own economies. While not conclusive, the observations suggest that some trading blocks and countries seem better at navigating the trade-off between maximizing effectiveness and minimizing domestic economic harm.

Lastly, we also shed some light on whether retaliation is effective. We first document that there are tangible economic implications of retaliation on trade flows. We document that US exports of goods to trade partners that imposed retaliation sharply decline. Our estimates suggest that between July and December 2018 at least 15 billion dollars of US exports were affected by the retaliation measures. We document that this is unlikely to capture just trade rerouting, as overall exports to the rest of the world do not increase and export price indices for sectors most affected by retaliation decrease substantially. This indicates that exposure to retaliation is likely to have produced a non-negligible income shock. Turning to whether retaliation was politically effective, we study the recent 2018 Midterm elections. Specifically, we analyze changes in the Republican party vote share for House and Senate seats between 2016 and 2018. A naive first-difference estimate suggests that there is no systematic reduction in support for Republican candidates in areas more exposed to retaliation. Yet, this observation is partly capturing the fact that retaliation is endogenous to how strongly an area swung in support for Trump in 2016. Once we control for this endogenous regressor, we observe moderate negative effects suggesting that Republican candidates fared worse by between 1.4 - 2.7 percentage points in counties that are in the top decile of the exposure distribution implied by the Chinese, Canadian and Mexican retaliation. Studying high frequency data on Presidential approval ratings, we further find some evidence that in areas exposed to retaliation, the approval ratings for Donald Trump deteriorate, in particular among self-identifying Democrats.

Our research speaks to the political effects of trade integration. Building on the seminal work by [Autor et al. \(2013\)](#), which documents that import competition due to trade-integration with lower income countries, in particular China, has accelerated secular decline in certain tradable-goods producing industries. This



work has motivated a significant literature which investigates the political implications of these economic shocks. [Autor et al. \(2016\)](#); [Che et al. \(2017\)](#); [Colantone and Stanig \(2018\)](#); [Dippel et al. \(2015\)](#) each document, in the context of the US, the UK and Germany, that areas most exposed to import competition are significantly more likely to become politically more extreme or polarized in elections. In fact, both [Autor et al. \(2016\)](#); [Che et al. \(2017\)](#) suggest that the election of Donald Trump, on a nativist America First platform, was significantly shaped by votes coming from areas that suffered most strongly from import competition with low income countries. Similarly, [Colantone and Stanig \(2018\)](#) suggests that areas most exposed to import competition saw distinctly higher levels of support for “Leave” in the 2016 EU Referendum.<sup>3</sup> Our results indicate that nativist policies themselves, by triggering retaliation of trading partners, may itself have non-negligible adverse economic effects and may trigger a political backlash, by virtue of the retaliation being highly targeted.

Our findings also contributes to the literature on the political economy of trade disputes. While models of trade policies have incorporated the role of domestic special interest groups (e.g. [Grossman and Helpman, 1994, 1995](#)), the potential impact of retaliatory measures have so far been neglected. Our results indicate that retaliatory measures can harm the electoral outcomes of politicians. Therefore, policy makers would need to consider the impact of likely retaliatory measures before making a decision on trade policy.

In other related research, economists have analyzed the economic and political targeting of sanctions (e.g. [Elliott and Hufbauer, 1999](#); [Eaton and Engers, 1992](#); [Ahn and Ludema, 2017](#)). While tariffs have been studied explicitly as an economic tool, sanctions have been understood as a purely politically motivated foreign policy tool to induce compliance. In this literature, [Marinov \(2005\)](#) and [Allen \(2008\)](#)

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<sup>3</sup>The distributional effect of trade integration may be mitigated by an active welfare state ([Stolper and Samuelson, 1941](#); [Rodrik, 1998](#); [Stiglitz, 2002](#)). In the context of Brexit, [Fetzer \(2018\)](#) suggest that the welfare state was responsive to mitigate the negative economic shocks due to trade integration, resulting in a significant rise in benefit recipients. The political backlash only emerged once the welfare state was significantly curtailed due to a broad austerity program, causing the backlash that Brexit poses.

provide evidence that sanctions increase the probability of leadership change. In other work, [Draca et al. \(2018\)](#) show that US sanction against Iran are effective in targeting politically connected firms and actors. Compared to sanction, retaliatory tariffs are a far more limited in scope and intensity. This could explain why the targeting of tariffs has played a smaller role in economic research. Nonetheless, our findings suggest that, similar to sanctions, retaliatory tariffs can be used to affect political outcomes.

The rest of the papers proceeds as follows. Section 2 describes the political context and the data used in the empirical analysis. Sections 3 presents the results on the extend of political targeting of tariffs. Afterwards, Section 4 provides evidence for the effectiveness of the political targeting. Section 5 analyzes different channels through which tariffs effect electoral outcomes. Section 6 concludes.

## 2 Context and Data

The international trading system after the second World War was first institutionalized through the General Agreement on Tariffs and Trade (GATT) in 1948. It was a direct result of the failings of the international trade system during the Great Depression. In 1930, the Smoot-Hawley Act increased tariffs on more than 20,000 products imported by the US. This set off a tit-for-tat retaliation dynamic. Canada – already at this time one of the US closest trading partners – imposed tariffs on 16 goods, which accounted for around 30% of US exports to Canada. [Irwin \(1998\)](#) estimates that nearly a quarter of the observed 40% decline in imports can be attributed to the rise in the US tariff and 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 e.g. to foster non-economic social policy objectives, to ensure “fair competition”, or to support preferential treatment of

developing countries, regional free trade areas and customs unions. But measures of this kind are subject to scrutiny, should adhere to the broad principles of the WTO and can be contested by WTO member countries by invoking the WTO's Dispute Resolution mechanism.

There are several historic examples which seem to indicate that trade policy, and in particular, tariffs may be a tool to alter the economic policy of countries. In 1971, President Nixon imposed a 10 percent tariff across the board in the hope of forcing Japan, Germany and some other countries to revalue their currencies. The tactic worked within months. In another instance, tariffs on Italian wine and French cheese in the 1980s helped to persuade the EU to put its Common Agricultural Policy on the negotiating table in the talks that created the World Trade Organization (WTO).

The most recent precedent in which the international trading system came close to a similar large scale escalations were due to steel tariffs, imposed by President George W Bush, which took effect March 20, 2003. The US justified the tariffs as an anti-dumping response and in contrast to the current spate, NAFTA partners were exempted from the tariff rise. The EU and other trading bodies and countries immediately filed a dispute with the WTO. On November 11, 2003 this resulted in a verdict against the US and tariffs were abolished on December 4, 2003. The WTO ruling implied that the anti-dumping justification for the tariffs was void, as the US had in fact been importing less steel compared to previous years in 2001 and 2002. The ruling authorized more than \$2 billion in sanctions against the US. President George W Bush initially wanted to preserve the tariffs. Though, following threats of retaliation by the European Union, the US 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 it may have played a role. The European Commission openly and transparently states the objectives it aims to achieve in the context of trade disputes. 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 minimizing harm to the own economy. To design the retaliation response, the European Commission is known to use an algorithm to select products against which retaliation tariffs are targeted. This algorithm is naturally a safely guarded secret.<sup>4</sup>

The Chinese government does not publish their policy objectives in the trade dispute, but there is evidence that they also try to target their tariffs against the electoral base of Donald Trump and the Republican party. For example, Chinese retaliation, similar to the EU’s retaliation basket, targeted goods, such as bourbon whiskey produced in the home state Kentucky, Mitch McConnell, the Senate majority leader. Similarly, the Wisconsin congressional district of the then Speaker of the House Paul D. Ryan was targeted with retaliatory tariffs on cranberries and cranberry products. Similarly, China (as well as Mexico) targeted pork and soybeans, with the latter being one of the most important US agricultural export to China, which disproportionately affected Iowa, the home state of influential Republican Senate Agriculture Committee member Senator Charles E. Grassley. In

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<sup>4</sup>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.

our analysis, we therefore investigate to what degree the retaliating countries were indeed able to politically target their retaliation. To do so, we create a measure for the exposure to retaliatory tariffs for each of US county, which we discuss next.

## 2.1 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 stemming from the US. 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.<sup>5</sup> For our analysis, we have obtained retaliation tariff lists from the EU, China, Mexico, Canada, Turkey and India. The detailed empirical analysis will focus on the EU, China and the NAFTA countries, due to the overall quite small trade volumes that were affected for Turkey and India. Appendix [A.1](#) provides more details and the exact links to the lists that we leverage in this paper.

We visualize the goods that were targeted by different trading blocks in Figure [A1](#). The figure plots word clouds containing words from the HS-10 titles of goods that were targeted with retaliatory tariffs. It is apparent that the different trading blocks targeted different product. For example, while the EU and Canada heavily targeted the US steel industry the Chinese retaliation focuses mainly on agricultural products (both frozen and fresh). Additionally, Appendix Figure [A2](#) visualizes the distribution of the retaliation measures across coarse economic sectors.<sup>6</sup> The figure suggests similarly, that manufacturing sector outputs, as well as agricultural commodities were significant features in the retaliation lists. We next describe how we use the retaliation list to construct a county's exposure to tariffs.

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<sup>5</sup>Appendix Figure [A3](#) is a screenshot from the EU's submission to the WTO.

<sup>6</sup>We merge the HS codes in the retaliation lists to NAICS sectors. The match of HS10 codes to six digit NAICS codes is based on the concordances constructed by [Schott \(2008\)](#).

## 2.2 Measuring county level exposure to retaliation

There are two key data sources that we use to construct a county level measure of exposure to a specific list of products  $\mathcal{L}_r$  subject to retaliation measures. First, we use data from the [Brookings \(2017\)](#) Export Monitor. This data constructs a measure of county-level exports across a set of 131 NAICS industries.<sup>7</sup> We denote  $X_{c,i}$  capturing, for each county  $c$  a measure of exports in industry  $i$ . In addition, the data also provides an estimate of the total exports at the county level and the number of export dependent jobs. The latter will be used to weight the regressions. Secondly, we use the individual retaliation lists  $\mathcal{L}_r$  for  $r \in \{EU, MX, CA, IN, TR\}$ . These are matched at the 8-digit HS level to the US trade data using export volume.<sup>8</sup> We validate our mapping by studying whether the resulting value of trade flows affected by tariffs is similar to those quoted in the official WTO submissions. For this exercise, we make use of HS-level U.S. import and export data from the U.S. Census Bureau.<sup>9</sup> In the case of the EU, the retaliation measures officially target trade worth USD 7.2 billion. Matching the EU list to the US trade data for 2017, we find that US exports worth USD 7.6 billion are affected by retaliation, suggesting that the overall magnitude is similar.

Next, we use the concordances between HS codes and NAICS/SIC codes constructed and made available by [Schott \(2008\)](#), to link the targeted exports to the different six digit NAICS sectors that produce the goods (HS10 codes). These concordances provide up to 10 digit commodity codes, which map into the Harmonized System codes used, together with SIC and NAICS codes, allowing us to merge these with the employment data. In case multiple sectors are linked to an

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<sup>7</sup>The data combines various data sources, including the USA Trade Online (Census) for goods exports, the Bureau of Economic Analysis (BEA) for services exports, the Internal Revenue Service (IRS) for royalties data along with Moody’s Analytics production estimates at the county level, and university level foreign students’ expenditures from NAFSA. More detailed description of this data is provided in Appendix A.2.

<sup>8</sup>While technically the codes of products are provided at the 10 digit level, the matching results are best at the 8-digit HS level due to slight discrepancies in the coding standard across countries. For example, the EU uses the Combined Nomenclature (CN), which uses the HS for the first 8 digits, further subdividing the coding to the 10 digit level that is specific to the EU. This introduces only a small amount of inconsequential noise.

<sup>9</sup>These data can be found here <https://usatrade.census.gov/>.

HS10 code, we retain the NAICS sector listed first in the concordance, producing a consistent one to one mapping. As an illustration, consider the example of the EU’s rebalancing measures, which includes the item “10059000 Maize (excluding seeds for growing)”. This HS code is mapped to the NAICS industry 111150, which stands for “Corn Farming”. This procedure results in a list of *tariff exposed industries*.

Afterwards, we collapse the total volume of affected trade to the four digit industry level. This gives us a measure of total export  $T_{i,r}$  affected by retaliatory tariffs of country  $r$  for each four digit industry  $i$ . We can break this measure down to the county level using  $X_{c,i}$ , the amount of production of industry  $i$  in county  $c$  as measured by the [Brookings \(2017\)](#) data. In other words, the total export volume affected by tariffs is broken down to the county-level using a county’s share of exports from industry  $i$ . This approach is thus similar to the more conventional [Autor et al. \(2013\)](#) type labor market shocks, with the exception that, rather than constructing this measure based on sector level employment figures, we are able to measure this based on sector level output figures, which should come closer to capturing the economic impact more broadly.

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

$$\tau_{c,r} = \sum_i \frac{\frac{X_{c,i}}{\sum_c X_{c,i}} \times T_{i,r}}{\sum_i X_{c,i}}$$

This measures approximates the impact of the retaliatory counties for each US county and therefore allows us to study the impact of these tariffs. The measure is bounded between 0 and 1. If all industries in a county are unaffected by tariffs the measure will be 0. If the entire production of a targeted good is taking place in a single county and the county produces only this good, the exposure measure would be 1.

As a real example of the exposure measure, consider the case of tariffs on whiskey, which was included in the retaliation measures from China, the EU and

Mexico. The US exported USD 713.1 million worth of whiskey to the EU, USD 7.2 million to Mexico and USD 2.2 million to China in 2017. Each of these three countries levied a 25% additional tariff on whiskey, resulting in a tariff cost of around USD 180.6 million on the sector. Whiskey is produced by the four digit sector “3121 - Beverage manufacturing”, meaning that areas producing output in this sector should be most affected. In total, this sector is estimated to export goods worth USD 7060.96 million.<sup>10</sup> Our measure allocates the tariff shock based on a county’s export volumes in 2017 and then normalizes this by the overall volume of exports from these counties. The top five counties that would appear as being affected by this retaliation are Nelson, Wythe and Madison in Virginia, Napa in California and another Nelson county in Kentucky. Four of these five counties have a significantly sized distillery sector and are significantly exposed to trade with, in particular, the EU. Yet, the example also highlights some limitations as Napa Valley in California is a “false positive” in the sense that it is a wine and not whisky producing area. It gets picked up, since wine is included in the “3121 - Beverage manufacturing” sector. Nevertheless, the approach seems to broadly produce accurate exposure measures.

## 2.3 Main outcome measures

For the second part of the paper we draw from multiple data sources to study political and economic implications of the retaliation measures more broadly.

### 2.3.1 Economic Impact Measures

To quantify the economic impact of the trade retaliation measures on trade flows, we construct a dataset capturing monthly US trade flows, particularly exports at the 10 digit HS code level mapping the level at which retaliation was issued.<sup>11</sup> Similarly, we collected additional data capturing Export Price Indices developed by the Bureau of Labor Statistics, which are released on a monthly basis. This data is available for around 90 different four digit NAICS sectors and

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<sup>10</sup>The EU targeted two whiskey types: Whisky, in containers holding  $\leq 2$  l (other than Bourbon whiskey and Scotch whisky) and Bourbon whiskey, in containers holding  $\leq 2$  l

<sup>11</sup>These data can be found here <https://usatrade.census.gov/>.



will help complement the analysis on trade flows. Specifically, since trade flows may simply be re-routed, it could be that the income implications of the tariff may be limited. Hence, studying export price indices may help shed light on whether tariffs actually did produce a negative income shock. Figure 1 presents the year on year changes in the export price indices of the US for agriculture and manufacturing sector outputs. Note that, these figures do not account for the different size of the relevant sectors, but the observed deterioration in export prices following July 2018 is evident, indicating that export prices did indeed collapse. We also test this in a more robust econometric framework later on.

### **2.3.2 Election and political outcome measures**

To investigate if retaliatory tariffs did affect political outcomes, we use Dave Leip's election data. This data capture US county-level election outcomes, specifically for the recent 2008, 2012, 2016 presidential elections as well as for the House and Senate elections, in particular, the 2018 midterm elections. We also incorporate data from Gallup through its Daily Tracker dataset, which will serve as an additional high frequency measure of popular support or approval for President Donald Trump, who is broadly seen as responsible for the escalation of the trade dispute.

We next investigate whether the chosen retaliation appears to have been systematically politically targeted.

## **3 Was the retaliation politically targeted?**

### **3.1 Descriptive evidence**

We first show simple descriptive evidence that counties with a stronger support for the Republican party were more heavily targeted by tariffs. In Figure 2 we plot the distribution of the exposure measure across US counties combining the retaliation measures across the different retaliation lists. Figure 3 provides the visualization across different countries or trading partners. This figure highlights that there is some variation e.g. when comparing China, the EU, or Canada and

Mexico. Similarly, in Panel A and Panel B of Figure 4 suggests a clear pattern whereby counties that are leaning towards the Republican party exhibit larger  $\tau_{c,r}$ , similarly, counties that saw bigger swings to Trump in 2016 (relative to the presidential candidate in 2012), have distinctly higher levels of the  $\tau_{c,r}$  measure. We will next explore this in a more robust regression framework.

### 3.2 Regression evidence

To understand to what extent retaliatory measures disproportionately targeted Republican counties within the US, we estimate the following regression equation:

$$y_{c,s} = \alpha_s + \beta_r \times \tau_{c,r} + \epsilon_c \quad (1)$$

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 changes 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 Section 2.2). The regression includes state fixed effects, hence we exploit within-state variation. Standard errors are clustered at the county level.

We further assess whether the targeting is *specific to areas* in which Donald Trump's markedly gained votes in the 2016 Presidential election. To do so, we take advantage of the three different election types in the data (Presidential elections, House elections, Senate elections) and estimate a heterogenous effect version of the above specification:

$$y_{c,e,s} = \alpha_{s,e} + \sum_{k \in H,S,P} \beta_{r,k} \times \mathbb{1}(ElectionType_e = k) \times \tau_{c,r} + \epsilon_c \quad (2)$$

Here,  $\alpha_{s,e}$  absorbs state by election type fixed effects. The specification allows us to distinguish whether areas that swung to Trump between 2016 and 2012 were differentially targeted, relative to areas, say, that increased support for Republican House candidates between 2016 and 2012. As it turns out, the observed patterns

suggest a quite distinct and sharp targeting of the retaliation measures against areas that markedly swung to support Trump, but did not swing to other Republican candidates for the House or the Senate in the same year on the same election day. This is indicative that the retaliation was carefully calibrated.

### 3.3 Results

The results from estimating model 1 are presented in Table 1. The strong and stable correlation suggests that counties which are more exposed to retaliatory tariff are more likely to have voted Republican in 2016 election. Further, the targeted counties are more likely to have significantly swung to the Republican party in the 2016 relative to earlier elections. In Appendix Table A1 we document that the association between tariffs is strongest for counties that voted for republican presidential candidates or swung to the republican presidential candidate between 2016 and 2012. This does suggest that political motivation play an important role when designing a retaliation bundle. Panel A allows for a direct comparison across the retaliation baskets for different countries, since the continuous retaliation measure  $\tau_{c,r}$  for each country is bounded between zero and one. This suggests that the degree of political targeting, both regarding the level of the Republican vote share in the 2016 Presidential election as well the change in the Republican candidate's vote share between 2012 and 2016 is strongest for the retaliation measures designed by the EU and Mexico.

In Panel B, we focus on a discretized measure of  $\tau_{c,r}$ , taking a value of 1 if a county is in the top decile of the retaliation list specific county level exposure distribution. Studying the top decile of counties exposed to retaliation suggests that Chinese retaliation is strongest, with the Republican party presidential candidate vote share in the top decile of counties affected by Chinese retaliation being nearly 17 percentage points higher compared to counties not exposed to the top decile of retaliation (column 2 of Panel B). For the EU, Mexican and Canadian retaliation the measures are comparable.

To highlight that the retaliation was designed to specifically target Donald Trump's voter base, we can sharpen the analysis further by studying election types.

If targeting is specific to Donald Trump (and not broadly the Republican party strongholds), we would expect that the targeting measure is distinct for areas that swung to Trump between 2012 and 2016, but not to areas that swung to Republican candidates for the Senate or the House more broadly between these two years. The results from this exercise are presented in Table 2. In columns (1) - (5) we study the continuous exposure measure, while columns (6) - (10) focus on the dummified measure. Panel A explores how targeting is correlated with different levels of support for Republican candidates across the House, Senate and Presidential elections in 2016. Throughout, there is a strong and positive correlation. Panel B focuses on studying to what extent is differentially targeted to areas that swung to support the Republican presidential candidate in 2016 (vis-a-vis 2012) and compared to the changes in support for Republican candidates in the House and Senate between these two years. The remarkable observation is that, throughout, the targeting is most strongly and distinctly correlated with areas that swung President Trump in 2016, but not for Republican candidates across other election types, despite the fact that voters could vote *on the same election day in 2016*. This strongly suggests that retaliation was indeed designed to hit areas that were swayed to support Trump in 2016 and may, conceivably swing back (for the literature studying the dynamics of US presidential and Midterm elections, see for example, [Alesina and Rosenthal, 1995, 2006](#) or [Scheve and Tomz, 1999](#)).

We next propose an alternative way of evaluating the degree of targeting in the design of the retaliation basket by simulating alternative retaliation baskets that conceivably could have been chosen.

## **4 Assessing the degree of targeting relative to simulated alternative retaliation baskets**

Is the observed targeting of Republican counties a mere artefact due to the mix of US export with specific trading partners? We investigate this hypothesis by constructing alternative retaliation baskets. Ideally, we would want to know the set of all possible retaliation baskets each country could have chosen. Unfortunately,

the choice of goods to retaliate against is a complex combinatorical problem, since goods can be chosen at the finely grained HS10 level. The choice of retaliation baskets is only constrained in the sense that it should match the value of the original tariffs by the US. For example, the tariffs imposed by the US on steel and aluminium affected around USD 7.2 billion of European Union exports to the United States (see Figure A3). As such, the EU’s measures should target a similar trade volume. Further, the tariff rate of the retaliation response is typically chosen to be of similar height than the initial tariff (in the case of the US it was 25% on steel and 10% on aluminium) or at least in our setting the initial retaliation response was chosen to be similar to the US rate.

Ideally, we would want to know all potential subsets  $\mathcal{S}$  of HS10 digit products codes such that a similar volume of US exports is targeted by retaliatory tariffs. In Appendix Figure A4, we visualize the number of different HS8 goods which the US is exporting to these markets. Hence, this is the number of goods from which the different countries could have chosen their retaliation responses.

## 4.1 Simulation approach

In computer science this kind of combinatorical problem is known as the *subset sum* problem. The challenge with subset sum problems is that they are NP-complete, meaning the most efficient algorithms to find a solution have 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 HS10 codes to choose from makes it computationally infeasible to derive the complete set of retaliatory baskets. Nevertheless, we can probabilistically simulate a set of alternative baskets, for each country’s retaliation list  $L$  using the following sampling procedure:

1. Randomly draw an integer number  $N_i$  providing the number of goods to be selected to be targeted — we allow for a 20% deviation from actual number of products that were chosen in the actual list
2. Draw a sample of size  $N_i$  different HS10 codes on which there is some exports

from the US in 2017

3. Compute the volume of trade that would be affected if this sample of goods was actually chosen for retaliation (allow 10% range around the actual value)
4. Repeat steps 1 – 3 until we found 1000 alternative baskets

As noted, this simulation procedure provides us with alternative bundles of goods that (conceivably) could have been chosen in the retaliation. While this is far from the full set, it is an approximation that allows us to study the targeting properties of the actual bundle relative to these counterfactual baskets. One potential drawback is that the simulation approach explicitly rules out the possibility that countries retaliating against the US may have coordinated their retaliation response. From the communication that the authors had with the European Commission, there are limited concerns that this has happened. The source in the EU only suggested that the Canadian government may have “copied” parts of the EU’s retaliation response.

## 4.2 Evaluating degree of political targeting

We next evaluate the degree of targeting relative to a set of counterfactual baskets. Specifically, we estimate regression model 1, except that we now instead use the county-level exposure measure  $\tau_{c,r}$  obtained from each of the 1000 alternative simulated goods baskets for each country specific list  $\mathcal{L}_r$ . The result of this exercise is a vector of estimates  $\hat{\beta}_r = (\hat{\beta}_r^1, \dots, \hat{\beta}_r^{1000})$  measuring the correlations between the simulated tariff exposure measure and, either the republican party Presidential election vote share in 2016 or its change between 2012 and 2016. We evaluate this against the  $\hat{\beta}_r^*$  for the actual list  $\mathcal{L}_r$ , by plotting the kernel density estimates of the different vectors  $\hat{\beta}_r$  indicating the estimate for the actual retaliation list as a vertical line  $\hat{\beta}_r^*$ . We additionally compute the amount of probability mass to the left of that estimate. We produce plots for both the Republican party presidential vote share in 2016 as well as the change in the Republican party vote share between 2016 and 2012. The results from this analysis are presented in Figure 5 for the dummified

retaliation exposure measure.<sup>12</sup>

The top panel of Figure 5 suggests that China achieved a very high degree of political targeting relative to the simulated baskets. However, China is also more constrained in its choice, as it is importing smaller variety of goods. If we for example exclude soy-beans, the bundle would appear much less politically targeted. The figure also suggests, that the European, Mexican and Canadian baskets, could have achieved a far higher degree of political targeting as is indicated by the relatively long tail to the right of the vertical line. On the other hand, the European basket appears to target areas that swung to the Republican party between 2012 and 2016. For this measure of targeting, 87% of simulated alternative basket exhibit a weaker degree of targeting than the actual basket.

### 4.3 Is there a tradeoff between political targeting and minimizing domestic economic harm?

As discussed in Section 2, the respective retaliation lists are likely the product of an optimization process that involves trade-off between various economic and political objectives. In particular the objectives of the European Union state, that retaliation should be effective while minimizing damage to the EU's own economy.

**Own country economic harm due to retaliation** To measure whether countries chose retaliation baskets in order to minimize the economic harm, we construct the share of US imports for a specific set of goods among all imports of this goods into a trading block. This measure proxies for the potential harm that retaliation poses for ones own economy. The intuition for this measure is that the cost to the own economy should be higher if the US is a major supplier, as the US appears to have a comparative advantage in providing these goods. Therefore, it may be difficult to find alternative sources of supply. We construct this measure using data from UN Comtrade, which provides trade data for almost all countries at the coarser HS6 level. This allows us to construct a HS6 goods specific US import share (relative to all imports) into a country or trading block.

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<sup>12</sup>Appendix Figure A9 presents the results for the non-dummified continuous measure, which are very similar, albeit having a much longer tail.

As before, we compute this share for all simulated retaliation bundles as well as the actual bundle. Afterwards, we again plot the kernel densities of these shares to visualize the distribution of US import share across products and retaliation baskets in Figure 6. The figure suggests that the EU appears to select the retaliation baskets that do not include goods in which the US has significant market share in the European market. The Chinese retaliation, on the other hand, does not seem to avoid goods for which the US has a significant market share. Also for Mexico and Canada, the exposure measure indicates that the chosen retaliation basket includes goods for which the US is a major supplier. This increases the probability that the retaliation response may have distinct negative economic repercussions on the Canadian and Mexican economies, that could potentially have been avoided. We next study whether such a trade-off exists, by studying the joint distribution of these measures together.<sup>13</sup>

**Tradeoff between political targeting and own country exposure** As we have constructed measures for the impact at home as well as the degree of political targeting in the US, we can study whether there is any trade-off between these two objectives. The optimal choice of a retaliation bundles should, conceivably maximize the effectiveness (as proxied by the degree of political targeting), while, at the same time limiting damage to the own economy. Though, the extent to which the two objectives play a role in designing the retaliation also, most likely depends on the national institutions and again, the extent to which countries can optimize this in designing their retaliation response, which is constrained by their respective degrees and depth of trade integration with the US.

We visualize this tradeoff, we plot the joint distribution of our two measures across the different retaliation bundles in Figure 7 studying the degree of targeting using level of Republican Presidential election vote shares in 2016, while Figure 8

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<sup>13</sup>The overall higher level of exposure for Mexico and Canada highlights that these countries are economically highly integrated, indicating that any retaliation will have significant implications for both their own markets. As the trade data is only available at the HS6 goods level, part of this overall higher level of exposure could be an artefact of the coarseness of the HS6 data. Yet, we would expect this to affect only the overall level of exposure, not the relative standing of the actual retaliation bundle.



studies the degree of targeting of changes in the Republican Presidential candidate vote shares between 2012 and 2016.<sup>14</sup> The horizontal axis measures the degree of political targeting that was plotted out in Figure 5. The average market share of the US across imports to a country across products, which was plotted in Figure 6, is shown on the vertical axis. The ideal location for a retaliation bundle should be in the lower right corner. Bundles in this corner both minimize domestic economic harm while maximizing the extent of political targeting. Contour lines of a bivariate kernel density of the joint distribution of these measures across the simulated retaliation bundles are indicated. This visualizes the set of potential choices available to countries. The figure further highlights mass points, which indicate how “difficult” it may be to arrive at an optimal bundle thereby illustrating the likely trade-offs.

The vertical- and horizontal lines in the figure indicate the measures associated with the actual bundle chosen. This allows us to assess how “optimal” the chosen retaliation bundles appear. Chinese retaliation is on the upper side with regard to the degree of political targeting; yet, China is performing quite poorly in avoiding damage to its own economy, since it retaliates against goods for which the US is a dominant supplier. Similarly for Canada and Mexico, the degree of political targeting is quite strong. In contrast, the EU appears particularly successful in identifying a retaliation basket that has a fair degree of political targeting, while at the same time, limiting the harm to its own economy.

One possible interpretation of this observation could be that the EU has a much more sophisticated approach in designing retaliation compared to the other countries. On the other hand, China, Mexico and Canada may be operating under less restrictive domestic political constraints relative to the clear objective and guidelines that constrain the EU (as we discussed in Section 2). Given that there appear to be a simulated baskets yielding the same degree of political targeting with lower

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<sup>14</sup>The measures plotted here are the distributions when studying the strength of retaliation focusing on the top decile counties for each of the country specific retaliation bundles. Appendix Figure A10 and Figure A11 highlight that the figure looks very similar when studying the degree of targeting focusing on the continuous county level retaliation exposure measure. Yet, for that measure the distribution is quite skewed.

implied potential harm for ones own economy, the analysis does suggest that the countries could have identified alternative retaliation baskets that achieve a similar degree of political targeting without the potential ramifications for their own economy.

Since the chosen baskets for each country appear in areas with weak support relative to the empirical distribution of the simulated counterfactual baskets, this suggests careful deliberation and calibration of the retaliation response. Yet, it also suggests that the degree of calibration may not optimize across the multiple potential trade-offs. A central question is whether retaliation is effective in producing economic pressures and, relatedly, whether it is effective in producing political pressures.

## 5 What are the economic effects of retaliation?

As a first measure of economic impact, we study the effects of retaliation on trade flows and export price indices. While reduced trade-flows could purely capture both trade-disruptions as well as trade-diversion, any impact of retaliatory tariffs on export price indices is likely to indicate tangible economic shocks.

### 5.1 Empirical specification

**Impact on exports** We first investigate the impact of retaliation on US trade flows. We use monthly US export data at the HS8 level to measure US exports to China, the EU, Canada and Mexico as well as the rest of the world. We then estimate the following difference-in-difference regression:

$$y_{r,h,t} = \alpha_{r,h} + v_{i,t} + \beta_r \times \text{Post July 2018} \times T_{h,r} + \epsilon_{h_4} \quad (3)$$

In this specification  $y$  measures US exports and the index  $r$  indicates the country which retaliated against the US.  $T_{h,r}$  is indicator variable which is 1 if good  $h$  was chosen to be included in the retaliation basket of country  $r$ . The regressions control for a range of shifters and fixed effects. Most importantly we include HS8 by trading country specific shifters  $\alpha_{c,h}$  capturing country  $r$  specific tastes for imports

from the US of goods  $h$ . We also control for destination country  $r$  specific time fixed effects as well as additional time fixed effects, indicated here by  $v_{i,t}$ . These additional time effects can be specific to a destination country  $r$  or, could account for good-specific seasonality. The latter is particularly relevant as US agricultural exports are highly seasonal.

**Impact on export prices** Secondly, we estimate the impact of retaliation on export price indices. This analysis is based on export price indices constructed for 46 NAICS4 sectors by the Bureau of Labor Statistics. We study to what extent sectors more exposed to retaliation measures saw a differential change in their export prices. To do so, we construct the exposure of a NAICS4 sector  $n$  to retaliation from country  $r$ , indicated as  $E_{n,r}$  as follows. Having merged the HS8 export data to NAICS codes, we compute the total volume of US exports in 2017 at the 4 digit NAICS level that would become subject to retaliatory tariffs from July 2018 by country  $r$  and divide this by the overall export volume. The tariff exposure measure across the 46 four digit industry groups for which it is constructed ranges from 0 to 34.6%, indicating that at the top 34.6% of exports produced by an industry was affected by tariffs. The average exposure measure is 5%. We then estimate the following regression:

$$y_{n,t} = \alpha_{n_j} + v_{i,t} + \beta_r \times \text{Post July 2018} \times E_{n,r} + \epsilon_{n,t} \quad (4)$$

The dependent variable measures the export price index at the four digit NAICS sector  $n$ . The sector fixed effects,  $\alpha_{n_j}$ , are at the level of the three digit sector or the four digit sector. Hence, we explore both within and between NAICS sector variation. We include time fixed effects throughout. Further, in some more demanding specifications we allow for time by first digit NAICS sector fixed effects. These first digit sectors broadly distinguish agriculture, mining and manufacturing. Standard errors are clustered at the four digit NAICS sector level. The main coefficient of interest is  $\beta_r$ . We would expect that this coefficient to be negative, indicating that after retaliatory measures came into effect, export price indices decrease for ex-

ports from sectors with a higher retaliation exposure  $E_{n,r}$ .

## 5.2 Results

**Impact on exports** The regression results are presented in Table 3. The point estimates in panel A suggest that exports that were exposed to retaliation shrank by around 75%. Panel B-E explores to what extent this result is robust to the exclusion of specific trading partner. It becomes obvious that, the Chinese retaliation, accounts for around 50-60% of the estimated contraction of US exports. This is expected since the Chinese retaliation was by far the most extensive given the structure of US trade with China. Nonetheless, also goods targeted by the EU, Canada and Mexico exhibit a significant reduction in exports to these markets.

Overall, the point estimate suggest that each month around USD 2.55 billion worth of exports have either not taken place or were diverted as a result of the tariff measures, amounting to around USD 15.28 billion in aggregate since the retaliation measures became effective in July 2018 until the end of 2018. Panel A in Figure 9 provides an event study version of specification 3, estimating separate coefficient for each pre-and post treatment month. The figure highlights the sharp contraction in export volumes since July 2018, when most retaliation measures became effective. In Appendix Figure A6, we estimate the event studies focusing on pairs of countries, studying the US exports to a specific country that retaliated and to the rest of the world with just these two series. The results highlight a strong degree of seasonality in exports of goods that were subject to retaliation by China, which captures the agricultural crop cycle across the US. Notably, the peak in exports that should occur around the summer failed to materialize as commodity exports fell significantly due to retaliation. The figure suggests significant contractions in bilateral exports relative to trade with the rest of the world across the dyads that were affected by the retaliatory measures.

These results do not preclude the possibility that most of this trade was re-routed and absorbed by other trading partners. Yet using the case of soybeans, a look at aggregate numbers suggests, that there is a net contraction of exports (see Appendix Figure A7). In other words, the exports to the rest of the world have not

absorbed the tariff-induced reduction in demand.

To show that the retaliatory tariffs likely also had a significant effect on incomes in areas that produce the affected commodities (and not just capture trade-rerouting), we next provide some evidence suggesting that US export price indices also significantly declined.

**Impact on export prices** Table 4 presents the results from this analysis. Since the data are aggregated into far coarser industry sectors, the point estimates are unsurprisingly more noisy. Nevertheless, the results suggest that export prices declined significantly in 4-digit NAICS sectors that were more exposed to retaliatory tariffs. Panel A studies the overall sector level retaliation exposure measure, while in Panels B - E, split the retaliation exposure measure by country. The findings indicate that, at the coarse four digit level, only the retaliation by China, Mexico and Canada had a significant effect on export price indices. To reiterate, this is not surprising given the coarseness of the export price indices data. The results also rely on variation between 4 digit NAICS sectors (in columns 1-3). When we fully focus on within sector variation over time (columns 4-6), the estimates are even more noisy.

To illustrate the timing of the effects, in Panel B of Figure 9 shows that the contraction in export price indices occurs at the time of the introduction of retaliatory measures, with export prices growing strongly in early 2018. This could partly highlight increased demand due to stockpiling.

Taken together, the evidence from exports as well as exports prices, indicates that the retaliatory tariffs did indeed, induce some economic harm on the effected sectors. In that sense the tariffs were effective. As the last piece, of our analysis we now investigate whether tariffs also had a political impact.

## 6 Did retaliation affect the 2018 Midterms?

Did retaliatory tariffs influence the 2018 Midterm election? While until today not all relevant data for the 2018 Midterm election is available, we attempt to provide a preliminary look at a some election related outcomes. In particular, we

study the effect of retaliatory tariffs on the Republican parties vote share in 2018 as well as the presidential approval rating.

## 6.1 Empirical Specification

**Impact on midterm election** To study the impact of the retaliatory tariffs on the vote share of the GOP we use a first-difference framework. More specifically, we study the changes in county level vote share for Republican candidates for elections of type  $e$  between the 2018 result and the most recent prior election (e.g. the 2016 House election). We estimate the following specification

$$\Delta y_{c,e} = \alpha_e + X_i' \xi + \beta_r \times \tau_{c,r} + \epsilon_c \quad (5)$$

where  $\beta_r$  captures the impact of retaliatory tariffs from country  $r$  on the Republican candidates vote share. We use the dummified retaliation exposure measure throughout. As the regression is in first differences, we can interpret it as a simple difference in difference. We include county level control variables  $X_i'$ , most importantly the extend a county swung to Trump between 2012 and 2016. As the retaliation was targeted towards these counties, this is most likely an important control to include. We further include election type fixed effects (House versus Senate) in all regressions. As before, the regressions are weighted by the number of export dependent jobs in a county.

**Impact on Presidential approval** We also leverage data from the Gallup Daily Tracker to study whether in areas exposed to retaliation, approval ratings for President Trump were affected. The data is an unbalanced respondents-level panel with information on the resident county of respondents. As the sampling is not representative at the county level, we do not absorb county level fixed effects, but rather focus on state level variation, adding a vector of individual level controls. The data also includes the individuals' party affiliation and is available for 2017 and up to 2018 including September 2018, thus providing three months of data

after retaliation was triggered. We estimate variants of the following specification

$$y_{i,p,c,s} = X_i' \gamma + \eta_{p,t} + \nu_r \times \text{Post July 2018}_t \times \tau_{c,r} + \beta_r \times \tau_{c,r} + \epsilon_s \quad (6)$$

The dependent variable  $y_{i,p,c,s}$  is an indicator whether individual  $i$  of party affiliation  $p$  (taking the values Democrat, Republican or Independent) living in county  $c$  in state  $s$  responds “approve” to the question “Do you approve or disapprove of the way Donald Trump is handling his job as president?”. The specification controls for a set of individual level controls  $X_i$ , particularly, state by party by educational attainment shifters, as well as gender by income group shifters. Further, the regression absorbs political affiliation specific time effects  $\eta_{p,t}$ . The coefficient of interest is the interplay between  $\nu_r$  and  $\beta_r$ . We expect the coefficient  $\nu_r$  to be positive, as areas exposed to retaliation are more likely to be leaning towards the republican party, and specifically, to Trump as we documented above. The coefficient  $\beta_r$  would capture the change in approval since July 2018. We estimate the above specification for the whole sample and by political affiliation to shed light which political affiliation group is driving any effects. As before, all regressions are weighted by the number of export dependent jobs in a county.

## 6.2 Results

We first discuss the results from studying the performance of Republican candidates in the 2018 Midterm elections. Table 5 reports the regression results for the estimation of Equation (5). The regression result without controls in Panel A suggest no significant reduction on the Republican vote share in counties that were more strongly targeted by retaliatory tariffs. The coefficients are negative for Chinese, Mexican and Canadian retaliation, but are statistically insignificant. This is not surprising: the analysis in section Section 3 suggests that targeting is endogenous to the extent to which areas swung to Trump between the 2012 and 2016 elections and the extent to which areas swung to Trump is likely to have an effect on the Midterm independently. Therefore the swing to Trump is likely an important omitted variable. In Panel B and C we add as additional control the

of the swing to Trump in the 2016 presidential elections either as a continuous measure or by including dummies for the quintiles. Once we control for the degree to which areas swung to Trump in 2016, we observe statistically significant coefficients for our retaliation exposure measures. The coefficient in column (1) indicates that the highly targeted areas exhibited 1.6 percentage point reduction in the Republican vote share. This effect is driven by the retaliation exposure to Chinese, Canadian and Mexican retaliation, suggesting that Republican candidates in counties most exposed to retaliation fared worse by between 1.4 - 2.7 percentage points. This lends some credence to the idea, that retaliatory tariffs to some extent might be effective in changing electoral results.

In Table 6 we present results for the Presidential approval ratings estimating Equation (6). The approval data are from the Gallup Daily Tracker, which is so far only available until September 2018, reducing the statistical power of the analysis. In Panel A, we study the whole sample of participants. Not surprisingly, the retaliation exposure measure is strongly positively related with higher levels of approval for Donald Trump, as is indicated by a positive estimated  $\hat{\beta}_r$ . This again suggests that targeting was closely calibrated to hit areas that saw distinctly higher levels of support for Donald Trump. Turning to the effect of retaliation on the approval ratings after July 2018, the estimated coefficient  $\hat{\nu}_r$  is negative, but statistically insignificant. Yet, this appears to be masking heterogeneous effects. In Panel B, we focus on the subsample of respondents who identify as Democrats. Here, there is quite clear evidence suggesting that retaliation is associated with lower approval ratings for Donald Trump's presidency with approval ratings among self-identifying Democrats in counties exposed to retaliation deteriorating by up to 3.1 percentage points. Yet, what is noteworthy is that Democrat-leaning respondents overall approval rating is very low, standing in whole self-identifying Democrats sample at just 5%.

Panel C focuses on the set of Republican respondents. Here, the coefficients are again negative but mostly insignificant throughout. Counties that were most affected by Chinese and EU retaliation however, see lower levels of support that



are just marginally significant or insignificant. Lastly, Panel D suggests that the Retaliation exposure measure is most strongly correlated with approval ratings for Donald Trump among self-identifying Independents. Turning to the impact of retaliation on changes in approval ratings, we observe that the estimated coefficient  $\hat{\nu}_r$  measure is weakly negative, but not statistically significantly correlated with lower approval ratings among this group of individuals.

Overall, this suggest that there may be some tangible political cost to Donald Trump stemming from individuals living in areas most affected by the retaliation. While the Midterm elections may partly have been affected or skewed by Republican candidates (and not Donald Trump) being on the ballot papers, the presidential approval results indicate that there could be direct political cost to Donald Trump among voters in areas most exposed to the retaliation.

## 7 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 analyze whether retaliatory tariffs indeed disproportionately targeted more Republican areas. To the best of our knowledge, we are also the first to empirically document the trade-off between the degree of political targeting and potential harm done to ones own economy. Our findings suggest that countries appear to put different weights on these two policy objectives. We then turn our attention to the economic as well as political impact of retaliatory tariffs. Thereby, our results provide new insights into the underlying choices faced by policy makers when the design retaliatory tariffs measures.

## References

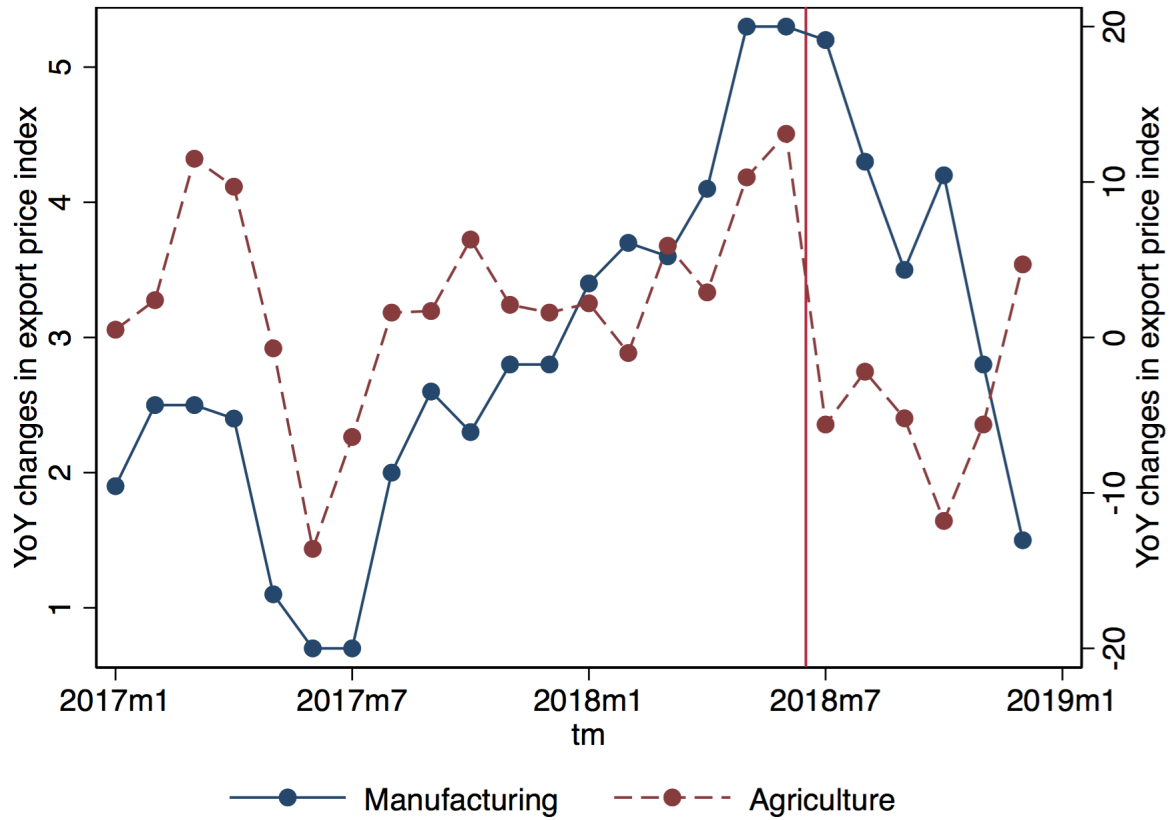
- Ahn, D. P. and R. D. Ludema (2017). *Measuring Smartness: Understanding the Economic Impact of Targeted Sanctions*. United States Department of State.
- Alesina, A. and H. Rosenthal (1995). *Partisan Politics, Divided Government and the Economy*. Cambridge University Press.
- Alesina, A. and H. Rosenthal (2006). A Theory of Divided Government. *Econometrica* 64(6), 1311.
- Allen, S. H. (2008). The domestic political costs of economic sanctions. *Journal of Conflict Resolution* 52(6), 916–944.
- Autor, D., D. Dorn, G. Hanson, and K. Majlesi (2016). Importing Political Polarization? The Electoral Consequences of Rising Trade Exposure. *CEPR Discussion Paper* 11511.
- Autor, D. H., D. Dorn, and G. H. Hanson (2013). The China Syndrome: Local labor market impacts of import Competition in the United States. *American Economic Review* 103(6), 2121–2168.
- 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*, Chapter 13.
- Bown, C. P. (2004). On the economic success of gatt/wto dispute settlement. *Review of Economics and statistics* 86(3), 811–823.
- Breuss, F. (2004). WTO Dispute Settlement: An Economic Analysis of Four EU US Mini Trade Wars. *Journal of Industry, Competition and Trade* 4(4), 275–315.
- Brookings (2017). Export Monitor. Technical report.
- Che, Y., Y. Lu, J. R. Pierce, P. K. Schott, and Z. Tao (2017). Did Trade Liberalization with China Influence U.S. Elections? *mimeo*.

- Colantone, I. and P. Stanig (2018, may). Global Competition and Brexit. *American Political Science Review* 112(02), 201–218.
- Dippel, C., R. Gold, and S. Heblich (2015). Globalization and Its (Dis-)Content: Trade Shocks and Voting Behavior. *NBER Working Paper 21812*.
- Draca, M., J. Garred, L. Stickland, and N. Warrinnier (2018). On target? the incidence of sanctions across listed firms in iran. Technical report, Competitive Advantage in the Global Economy (CAGE).
- Eaton, J. and M. Engers (1992). Sanctions. *Journal of Political Economy* 100(5), 899–928.
- Elliott, K. A. and G. C. Hufbauer (1999). Same song, same refrain? economic sanctions in the 1990's. *American Economic Review* 89(2), 403–408.
- Fetzer, T. (2018). Did Austerity Cause Brexit ? *CAGE Working Paper*.
- Frankel, J. A. and D. H. Romer (1999). Does trade cause growth? *American economic review* 89(3), 379–399.
- Gould, D. M. and G. L. Woodbridge (1998). The political economy of retaliation, liberalization and trade wars. *European Journal of Political Economy* 14(1), 115–137.
- Grossman, G. M. and E. Helpman (1994). Protection for sale. *American Economic Review* 84(4), 833–850.
- Grossman, G. M. and E. Helpman (1995). Trade wars and trade talks. *Journal of political Economy* 103(4), 675–708.
- Heckscher, E. and B. Ohlin (1933). Interregional and international trade. *Harvard University Press, Cambridge, MA*.
- Irwin, D. A. (1998, may). The Smoot-Hawley Tariff: A Quantitative Assessment. *Review of Economics and Statistics* 80(2), 326–334.

- Maggi, G. and A. Rodriguez-Clare (1998). The value of trade agreements in the presence of political pressures. *Journal of Political Economy* 106(3), 574–601.
- Marinov, N. (2005). Do economic sanctions destabilize country leaders? *American Journal of Political Science* 49(3), 564–576.
- Ossa, R. (2014, dec). Trade Wars and Trade Talks with Data. *American Economic Review* 104(12), 4104–4146.
- Ricardo, D. (1891). *Principles of political economy and taxation*. G. Bell.
- Rodrik, D. (1998). *Has Globalization Gone Too Far?*, Volume 41. Peterson Institute for International Economics.
- Scheve, K. and M. Tomz (1999). Electoral surprise and the midterm loss in US congressional elections. *British Journal of Political Science* 29(3), 507–521.
- Schott, P. K. (2008). The relative sophistication of Chinese exports. In *Economic Policy*, Volume 23, pp. 5–49.
- Stiglitz, J. (2002). *Globalization and its Discontents*. Penguin.
- Stolper, W. F. and P. A. Samuelson (1941, nov). Protection and Real Wages. *The Review of Economic Studies* 9(1), 58–73.
- WTO (2018). GATT disputes : 1948-1995. Technical report, World Trade Organization, Geneva, Switzerland.

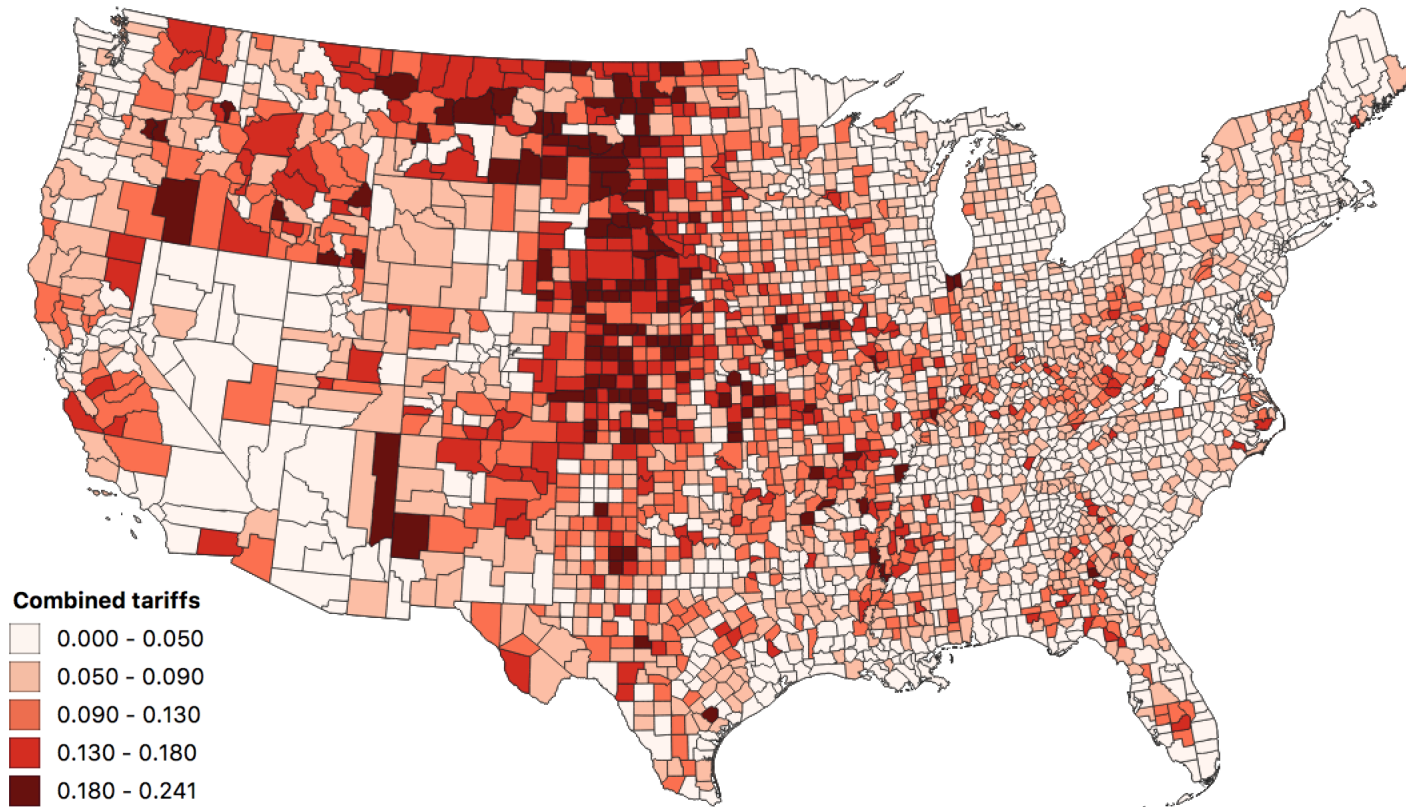
## Tables and Figures for Main Text

Figure 1: Year on year changes in export price indices for manufacturing and agricultural sectors



**Notes:** Figure plots the year on year changes in the export price indices for the manufacturing and agricultural sector series. The underlying data is from the Bureau of Labor Statistics and is released in monthly intervals.

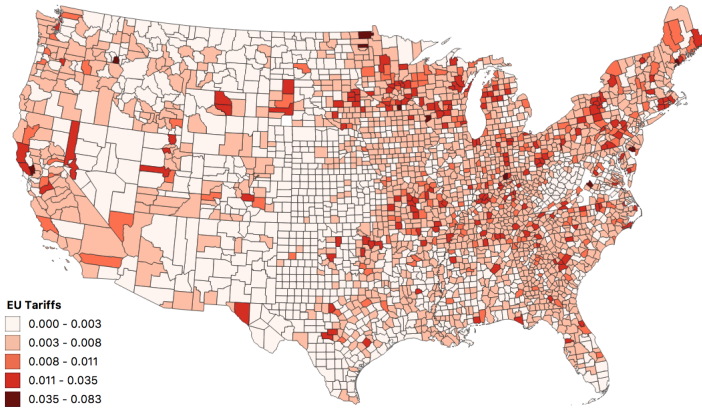
Figure 2: Distribution of share of county level export trade volumes affected by retaliation measures by the EU, China, Canada, Mexico, Turkey and India.



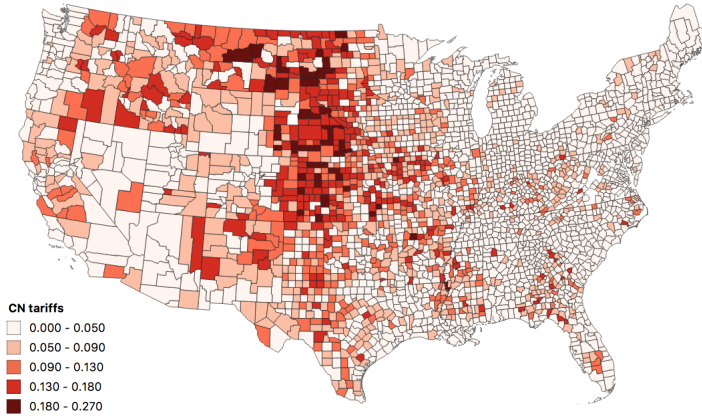
Notes: Map plots the quintiles of the county level exposure measure to retaliation from all retaliating countries combined. The construction of the exposure measure is described in more detail in Section 2.2.

Figure 3: Distribution of share of county level export trade volumes affected by retaliation measures by the EU, China, Canada and Mexico

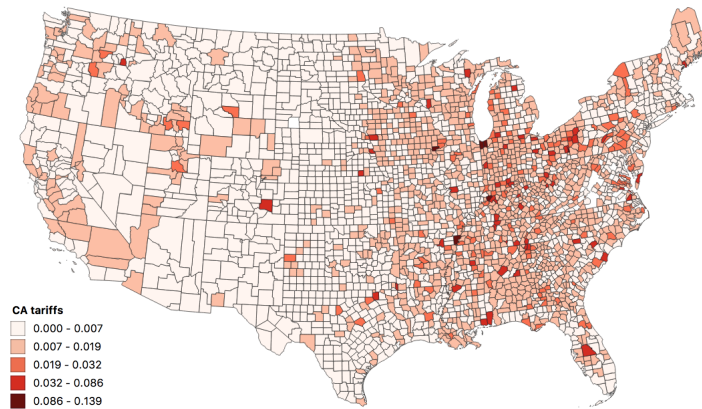
European Union



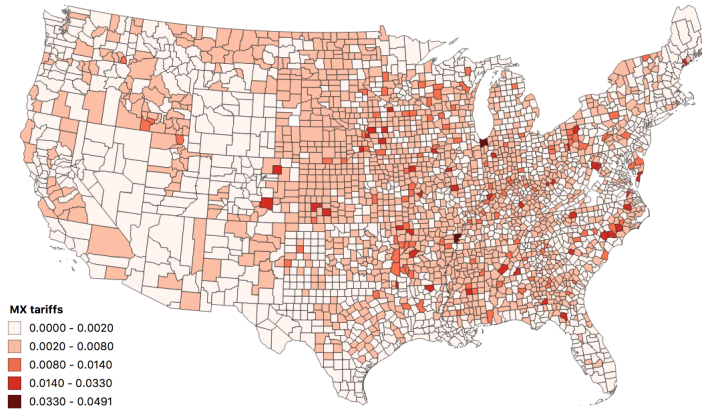
China



Canada



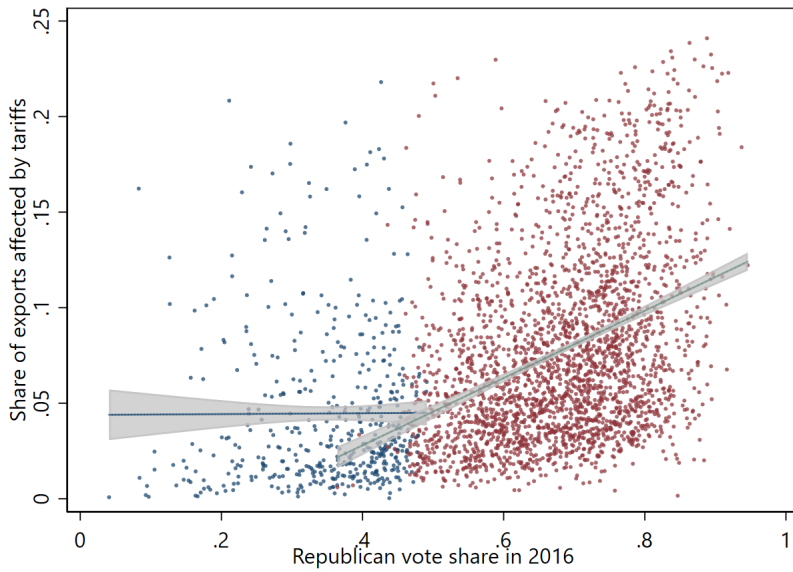
Mexico



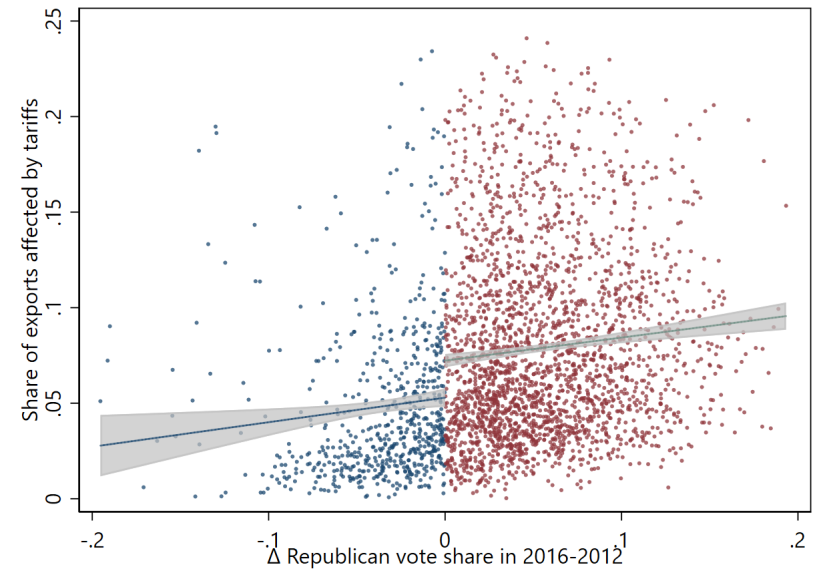
Notes: Map plots the quintiles of the county level exposure measure to retaliation from the respective countries. The construction of the exposure measure is described in more detail in Section 2.2.

Figure 4: County level export share exposed to tariffs and retaliatory tariff exposure

Panel A: GOP vote share in 2016



Panel B:  $\Delta$  GOP vote share in 2016-2012

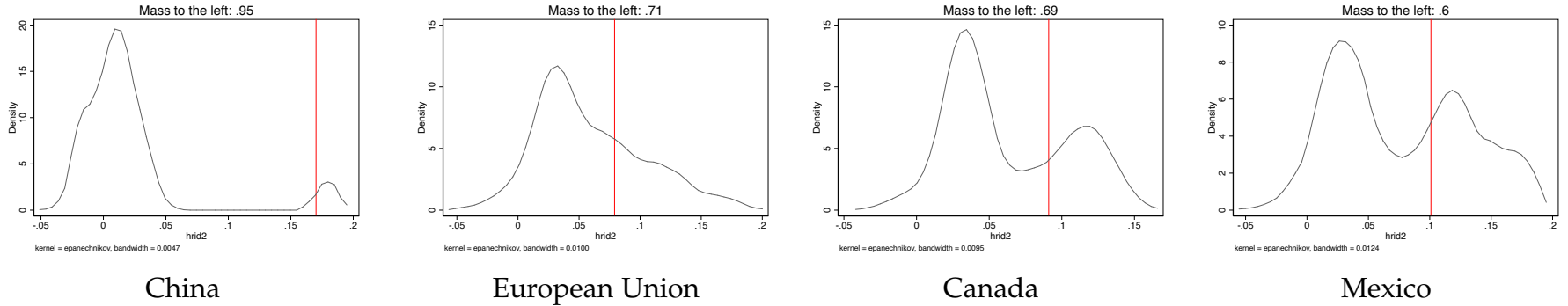


**Notes:** Figure plots the Republican party vote share in the 2016 Presidential election on the horizontal axis in Panel A and the change in the Republican party vote shares between the 2016 and 2012 Presidential elections at the county level in Panel B against the overall share of a county's exports that are exposed to retaliation by all countries.



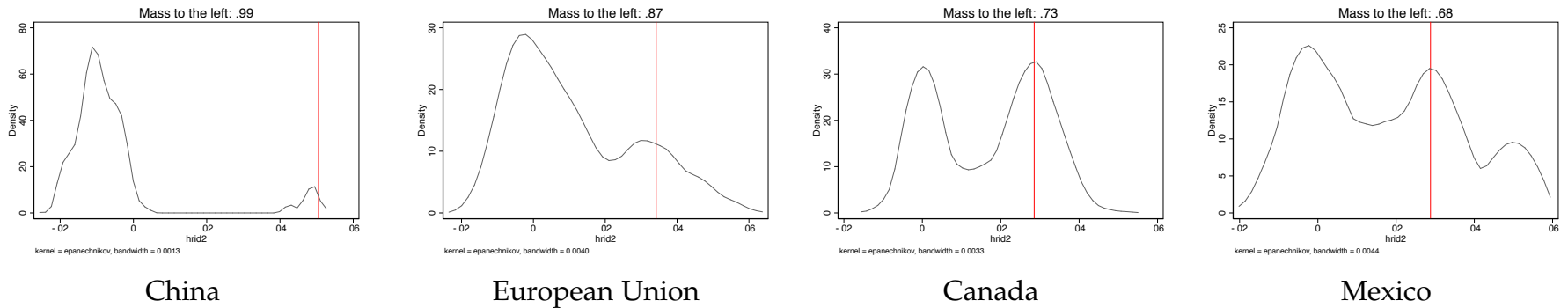
Figure 5: Was retaliation targeted? Probabilistic simulation of alternative retaliation goods baskets and the resulting county level exposure measure.

Panel A: GOP vote share in 2016



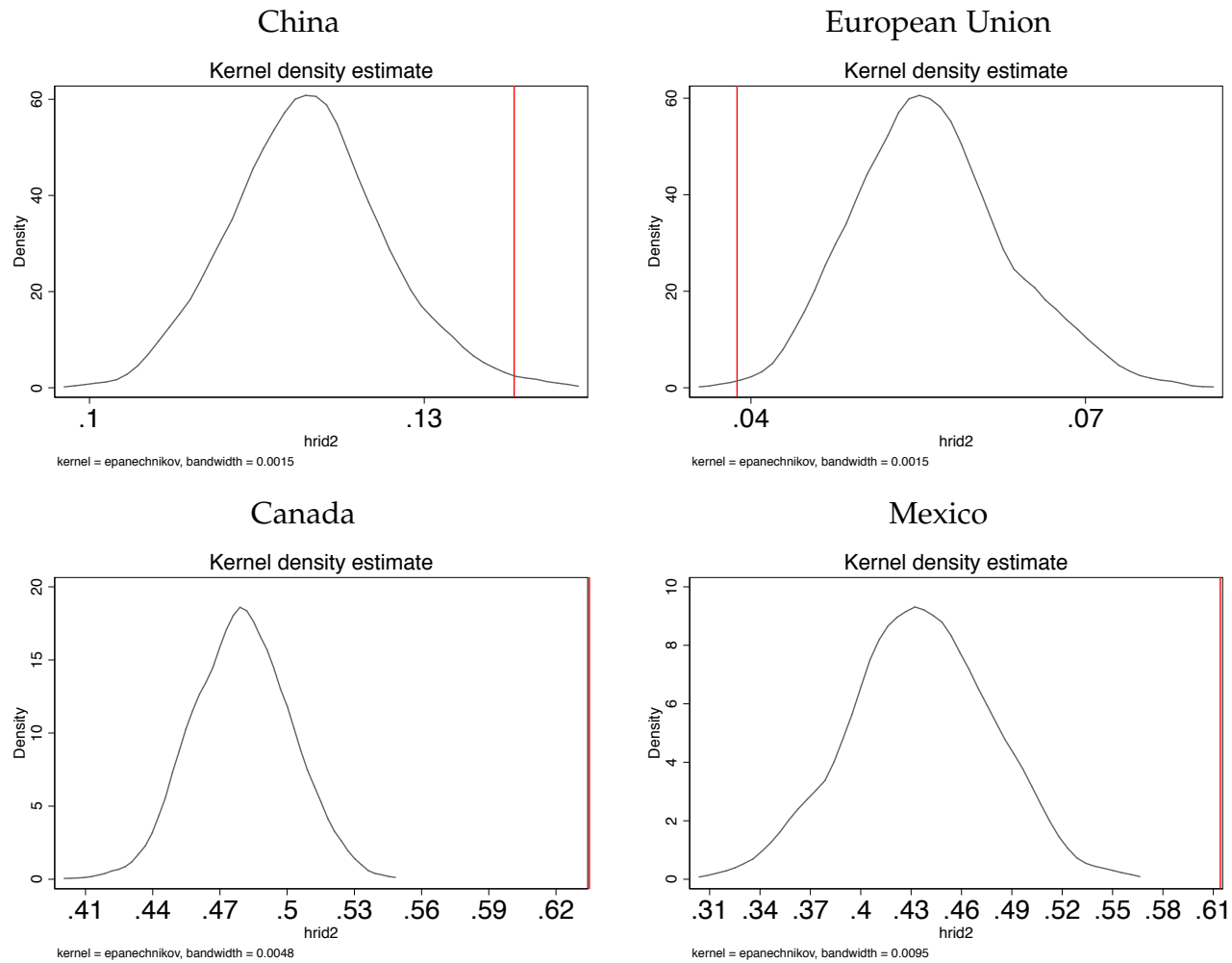
38

Panel B: ΔGOP vote share



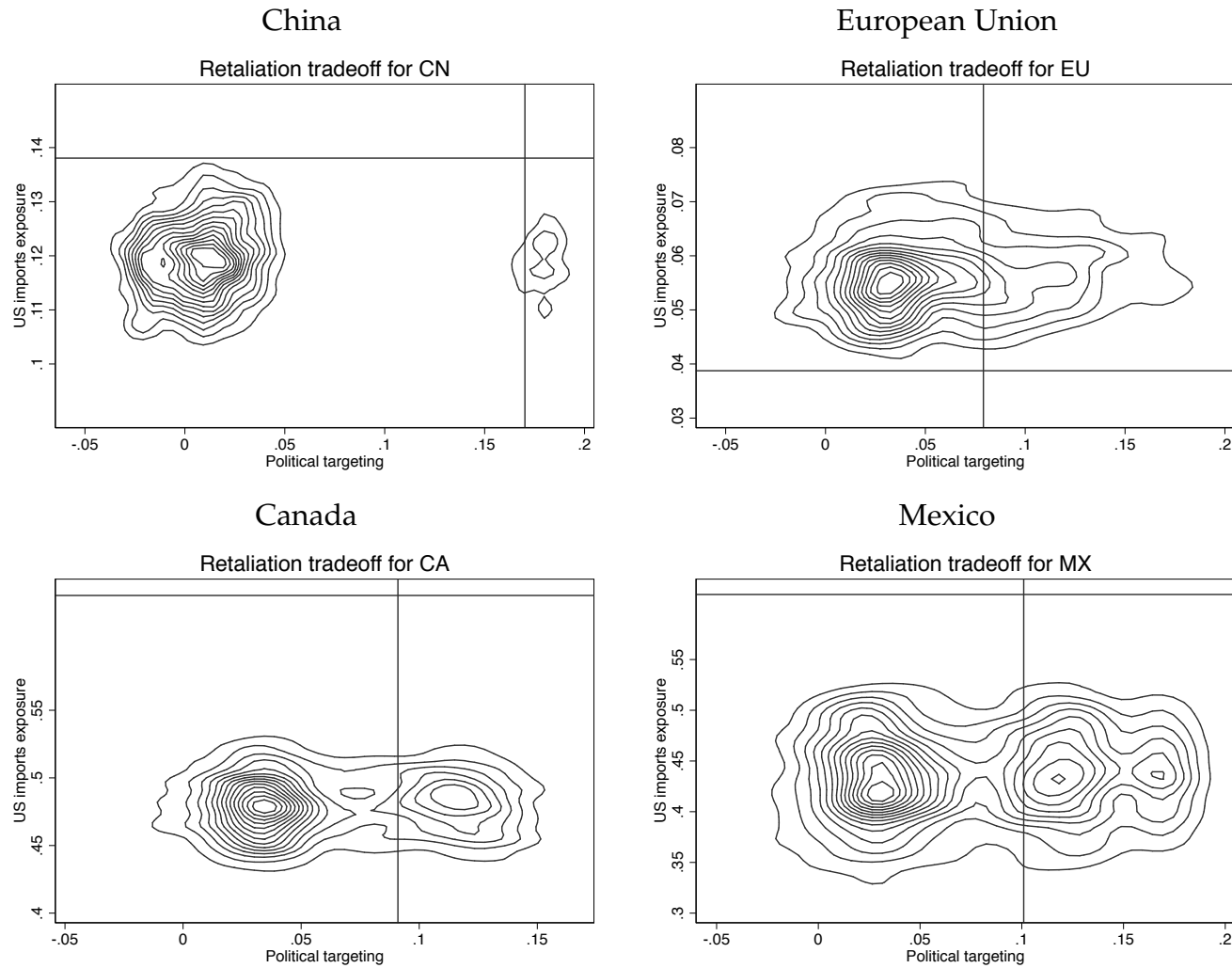
**Notes:** Figure plots kernel densities of the distribution of point estimates obtained from regressing the the GOP vote share or the change in the GOP vote share between the 2016 and 2012 presidential election on an indicator of whether the county is in the upper decile of the exposure to retaliatory tariffs from China, the EU, Canada or Mexico. Counties are weighted by the total number of export dependent jobs. The different point estimates are obtained from 1000 alternative baskets of HS10 codes that could have been chosen to achieve a similar amount of rebalancing compared to the actual basket chosen. The effect of the actual basket is plotted as a vertical line with the probability mass indicated to the left provided.

Figure 6: Trade-offs involved in designing retaliation measures – distribution of implied average US import penetration across HS6 goods baskets chosen for retaliation.



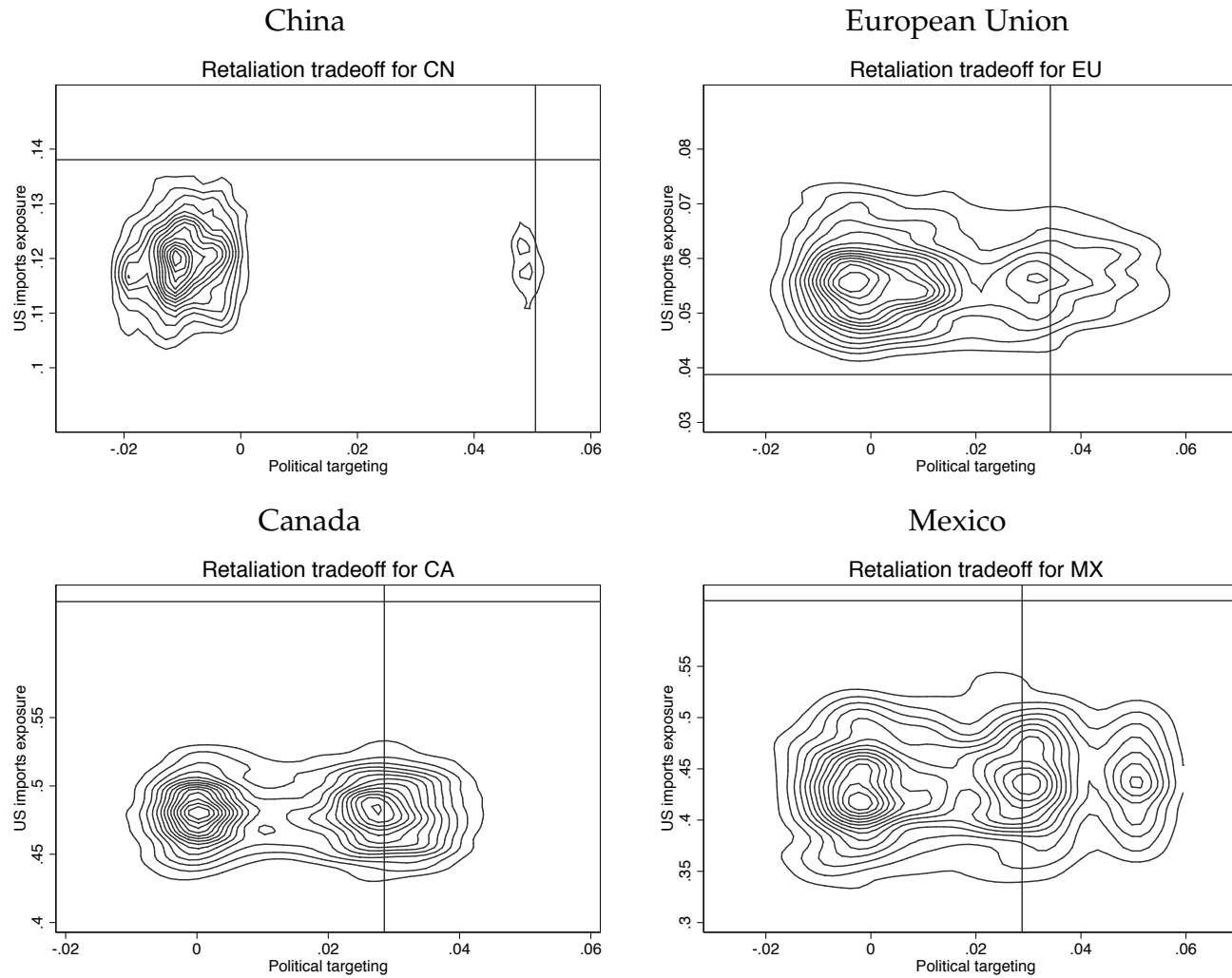
**Notes:** Figure plots kernel densities of the distribution of point estimates obtained from regressing the share of US imports in specific HS6 goods relative to a country or trading bodies overall imports for this specific HS6 good against an indicator variable capturing whether that good (or set of goods) is included in the actual retaliation basket (vertical line) or in one of the 1000 simulated counterfactual baskets that could have been chosen.

Figure 7: Trade-off in political targeting and exposure to US imports: GOP vote share in 2016.



**Notes:** Figure combines Figure 5 and Figure 6 plotting kernel densities of the joint distribution the two measures across the 1000 simulated retaliation baskets. Areas in the lower right corner indicate high degrees of political targeting of an specific retaliation basket and a low degree of (potential) domestic economic harm. The implied values for the actual baskets are indicated as horizontal and vertical lines.

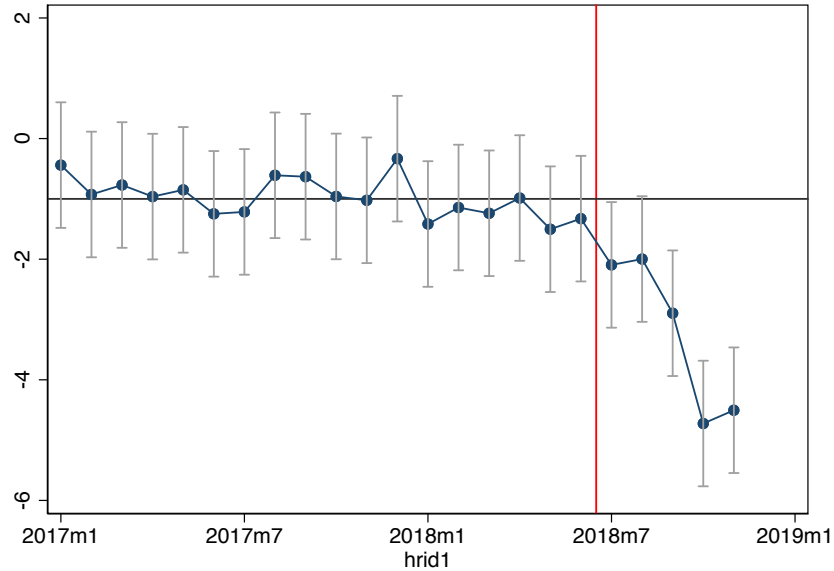
Figure 8: Trade-off in political targeting and exposure to US imports:  $\Delta$ GOP vote share 2012-2016.



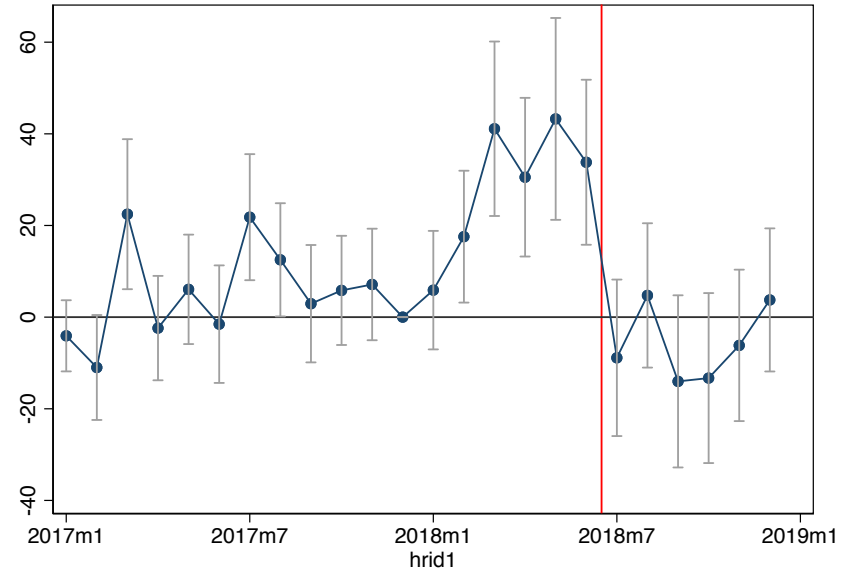
**Notes:** Figure combines Figure 5 and Figure 6 plotting kernel densities of the joint distribution the two measures across the 1000 simulated retaliation baskets. Areas in the lower right corner indicate high degrees of political targeting of an specific retaliation basket and a low degree of (potential) domestic economic harm. The implied values for the actual baskets are indicated as horizontal and vertical lines.

Figure 9: Did retaliation affect trade flows and export prices?

Panel A: US exports



Panel B: US export price indices



**Notes:** Figure plots estimates from a difference-in-difference regressions. Panel A presents point estimates capturing the evolution of exports from the US to EU, China, Canada, Mexico and the ROW over time on goods targeted by retaliation. The underlying regressions control for HS8 code by destination shifters, destination by time fixed effects and targeted sector specific seasonality. Standard errors are clustered at the 4 digit HS code level. The right Panel B presents results from a regression studying 46 export price indices constructed at four digit NAICS level. The plot presents point estimates capturing the evolution of export price indices over time as a function of the 4 digit NAICS sectors exposure to retaliation measures as the share of exports in 2017 at the NAICS4 level that was exposed to retaliation measures. The underlying regressions control for NAICS4 export price index fixed effects and time fixed effects; regressions are weighted by the 2017 overall export volume and standard errors are clustered at the NAICS4 level. 90% confidence bands are indicated.

Table 1: Measuring degree of political targeting of retaliation measure studying GOP electoral performance in 2016

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	2016 GOP vote share					$\Delta$ GOP vote share				
	Retaliatory tariffs imposed by...					Retaliatory tariffs imposed by...				
	Combined	CN	EU	CA	MX	Combined	CN	EU	CA	MX
<i>Panel A: Continuous exposure measure</i>										
Retaliation exposure	2.634*** (0.302)	3.483*** (0.250)	9.585*** (1.764)	2.767** (1.347)	7.883** (3.676)	0.783*** (0.071)	0.939*** (0.071)	3.207*** (0.485)	1.098*** (0.317)	2.979*** (0.834)
Observations	3108	3108	3108	3108	3108	3108	3108	3108	3108	3108
Counties	3108	3108	3108	3108	3108	3108	3108	3108	3108	3108
Mean of DV	.426	.426	.426	.426	.426	-.0184	-.0184	-.0184	-.0184	-.0184
<i>Panel B: Dummified exposure measure</i>										
Retaliation exposure	0.117*** (0.013)	0.171*** (0.017)	0.081*** (0.018)	0.092*** (0.017)	0.103*** (0.017)	0.035*** (0.004)	0.051*** (0.005)	0.031*** (0.006)	0.029*** (0.005)	0.029*** (0.005)
Observations	3108	3108	3108	3108	3108	3108	3108	3108	3108	3108
Counties	3108	3108	3108	3108	3108	3108	3108	3108	3108	3108
Mean of DV	.426	.426	.426	.426	.426	-.0184	-.0184	-.0184	-.0184	-.0184
State by Election Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is either the republican vote share in 2016 in columns (1) - (5) and the change in republican party vote share between 2016 and the most recent comparable election (2012 for Presidential election, 2014 for House Elections and various for Senate) in columns (6) - (10). The independent variable measures the county level retaliation exposure to retaliation from the countries or trading blocks indicated in the column heads. In Panel A the continuous measure is used, while in Panel B the dummified version is used where the retaliation indicator is equal to 1 if a county level exposure measure is in the top decile. All regressions include state by election fixed effects. Counties are weighted by the 2016 number of jobs that depend on exports. Standard errors are clustered at the county level and are presented in parentheses, stars indicate \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Table 2: Comparing degree of political targeting exploring GOP performance across *election types*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Retaliation exposure measure	Continuous measure					Top decile of counties				
	Combined	Retaliatory tariffs imposed by...				Combined	Retaliatory tariffs imposed by...			
		CN	EU	CA	MX		CN	EU	CA	MX
<i>Panel A: GOP 2016 vote share</i>										
President × Retaliation exposure	2.634*** (0.302)	3.483*** (0.250)	9.585*** (1.765)	2.767** (1.348)	7.883** (3.677)	0.117*** (0.013)	0.171*** (0.017)	0.081*** (0.018)	0.092*** (0.017)	0.103*** (0.017)
House × Retaliation exposure	2.458*** (0.457)	3.550*** (0.294)	8.809*** (2.175)	1.427 (2.036)	4.220 (5.500)	0.125*** (0.018)	0.147*** (0.024)	0.087*** (0.026)	0.086*** (0.027)	0.105*** (0.027)
Senate × Retaliation exposure	1.368*** (0.255)	1.928*** (0.230)	7.008*** (1.805)	1.027 (0.941)	3.466 (2.762)	0.082*** (0.014)	0.124*** (0.017)	0.058*** (0.017)	0.050*** (0.019)	0.065*** (0.019)
Observations	8099	8099	8099	8099	8099	8099	8099	8099	8099	8099
Counties	3109	3109	3109	3109	3109	3109	3109	3109	3109	3109
Mean of DV	.42	.42	.42	.42	.42	.42	.42	.42	.42	.42
<i>Panel B: Δ GOP 2016 to 2012</i>										
President × Retaliation exposure	0.783*** (0.071)	0.939*** (0.071)	3.207*** (0.485)	1.098*** (0.317)	2.979*** (0.835)	0.035*** (0.004)	0.051*** (0.005)	0.031*** (0.006)	0.029*** (0.005)	0.029*** (0.005)
House × Retaliation exposure	0.409** (0.199)	0.722*** (0.135)	1.463 (0.923)	-0.328 (0.871)	-0.931 (2.318)	0.026*** (0.010)	0.031** (0.015)	0.008 (0.013)	0.013 (0.015)	0.018 (0.017)
Senate × Retaliation exposure	-0.497** (0.248)	-0.861** (0.386)	-0.970 (1.501)	-0.297 (0.268)	-0.875 (0.676)	0.010 (0.007)	0.026* (0.014)	0.009 (0.009)	0.003 (0.008)	0.003 (0.007)
Observations	6930	6930	6930	6930	6930	6930	6930	6930	6930	6930
Counties	3109	3109	3109	3109	3109	3109	3109	3109	3109	3109
Mean of DV	-0.0178	-0.0178	-0.0178	-0.0178	-0.0178	-0.0178	-0.0178	-0.0178	-0.0178	-0.0178
State by Election Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is either the republican vote share in 2016 in Panel A, the change in republican party vote share between 2016 and the most recent comparable election (2012 for Presidential election, 2014 for House Elections and various for Senate) in Panel B and the change in republican party vote share between 2016 and the 2012 Presidential election or the 2012 House or Senate elections (if applicable). The independent variable is the dummified county level retaliation exposure to retaliation from the countries or trading blocks indicated in the column heads. All regressions include state by election type fixed effects. Counties are weighted by the 2016 number of jobs that depend on exports. Standard errors are clustered at the county level and are presented in parentheses, stars indicate \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Table 3: Did retaliation affect trade flows?

	(1)	(2)	(3)	(4)
<i>Panel A: Overall</i>				
Post July 2018 × Targeted	-2.696** (1.099)	-2.473** (1.061)	-3.077** (1.564)	-2.259 (1.520)
Observations	1690297	1690297	1690297	1690297
Clusters	1231	1231	1231	1231
Mean of DV	3.57	3.57	3.57	3.57
<i>Panel B: Excluding China</i>				
Post July 2018 × Targeted	-1.136*** (0.239)	-0.970*** (0.205)	-0.813*** (0.147)	-0.900*** (0.169)
Observations	1352226	1352226	1352226	1352226
Clusters	1231	1231	1231	1231
Mean of DV	4.11	4.11	4.11	4.11
<i>Panel C: Excluding EU</i>				
Post July 2018 × Targeted	-3.113** (1.341)	-2.851** (1.305)	-3.584* (1.926)	-2.527 (1.870)
Observations	1352226	1352226	1352226	1352226
Clusters	1231	1231	1231	1231
Mean of DV	3.63	3.63	3.63	3.63
<i>Panel D: Excluding CA</i>				
Post July 2018 × Targeted	-3.127** (1.402)	-2.858** (1.365)	-3.740* (2.014)	-2.677 (1.957)
Observations	1352284	1352284	1352284	1352284
Clusters	1231	1231	1231	1231
Mean of DV	3.64	3.64	3.64	3.64
<i>Panel E: Excluding MX</i>				
Post July 2018 × Targeted	-2.818** (1.166)	-2.580** (1.125)	-3.225* (1.659)	-2.362 (1.613)
Observations	1352226	1352226	1352226	1352226
Clusters	1231	1231	1231	1231
Mean of DV	3.75	3.75	3.75	3.75
HS8 x Dest FE	Yes	Yes	Yes	Yes
Time FE	Yes	No	No	No
Destination x Time FE	No	Yes	Yes	Yes
Targeted goods x Seasonality	No	No	Yes	Yes
HS8 x Dest Linear trends	No	No	No	Yes

Notes: The dependent variable is the level of US exports at the HS8 level by month. Standard errors are clustered at the 4-digit HS good level with stars indicating \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .



Table 4: Did retaliation affect export price indices?

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A: Overall</i>						
Post July 2018 × Tariff exposure	-69.846* (38.544)	-123.752 (73.983)	-102.670* (60.928)	-20.307** (8.510)	-11.027 (20.085)	-30.793*** (8.243)
Observations	1576	1540	1576	1576	1540	1576
Clusters	46	45	46	46	45	46
Mean of DV	114	114	114	114	114	114
<i>Panel B: Focusing on China</i>						
Post July 2018 × Tariff exposure	-17.524** (7.936)	-76.255** (36.448)	-29.218* (16.850)	-9.834*** (1.825)	-16.799 (13.202)	-13.745*** (1.086)
Observations	1576	1540	1576	1576	1540	1576
Clusters	46	45	46	46	45	46
Mean of DV	120	121	120	120	121	120
<i>Panel C: Focusing on EU</i>						
Post July 2018 × Tariff exposure	-1.421 (14.192)	-1.557 (14.259)	-4.926 (18.552)	-0.805 (5.954)	-0.968 (6.001)	0.133 (4.079)
Observations	1576	1540	1576	1576	1540	1576
Clusters	46	45	46	46	45	46
Mean of DV	113	113	113	113	113	113
<i>Panel D: Focusing on CA</i>						
Post July 2018 × Tariff exposure	-49.205*** (12.369)	-49.864*** (12.549)	-61.930*** (14.321)	4.626 (4.086)	4.057 (4.070)	1.712 (4.256)
Observations	1576	1540	1576	1576	1540	1576
Clusters	46	45	46	46	45	46
Mean of DV	111	111	111	111	111	111
<i>Panel E: Focusing on MX</i>						
Post July 2018 × Tariff exposure	-90.663* (46.142)	-88.239* (47.779)	-101.585** (40.790)	-10.194 (13.219)	-4.843 (10.288)	-41.953 (27.358)
Observations	1576	1540	1576	1576	1540	1576
Clusters	46	45	46	46	45	46
Mean of DV	110	110	110	110	110	110
Base Fixed effects	NAICS3	NAICS3	NAICS3	NAICS4	NAICS4	NAICS4
NAICS1 × Time FE	No	Yes	No	No	Yes	No
Linear Time trend	No	No	NAICS3	No	No	NAICS4

Notes: All regressions include time fixed effects. The dependent variable is the 4 digit NAICS sector level export price index constructed by the Bureau of Labor Statistics. The tariff-exposure measures the share of 4-digit NAICS sector exports measured in 2017 affected by retaliation. In Pane B- E, the retaliation exposure measure is constructed focusing solely on the respective trading block. Regressions are weighted by the overall level of exports in 2017 at the 4-digit NAICS level. Standard errors are clustered at the 4-digit NAICS sector with stars indicating \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Table 5: Performance of GOP in 2018 versus 2016 and exposure to retaliation measures

	(1)	(2)	(3)	(4)	(5)
	Retaliatory tariffs imposed by...				
	Combined	CN	EU	CA	MX
<b>Panel A: Average effect</b>					
House × Retaliation exposure	-0.012 (0.011)	-0.014* (0.008)	0.007 (0.014)	-0.015 (0.018)	-0.023 (0.021)
Senate × Retaliation exposure	0.005 (0.007)	0.011 (0.011)	0.014* (0.008)	-0.009 (0.008)	-0.007 (0.008)
Observations	5005	5005	5005	5005	5005
Counties	3001	3001	3001	3001	3001
Mean of DV	-0.0351	-0.0351	-0.0351	-0.0351	-0.0351
<b>Panel B: Controlling for 2012-2016 GOP swing</b>					
House × Retaliation exposure	-0.021** (0.011)	-0.025*** (0.008)	0.000 (0.013)	-0.023 (0.017)	-0.030 (0.021)
Senate × Retaliation exposure	-0.005 (0.006)	-0.002 (0.011)	0.007 (0.007)	-0.019*** (0.007)	-0.016** (0.007)
$\Delta GOP_{2012}^{2016}$	0.185*** (0.051)	0.162*** (0.052)	0.158*** (0.050)	0.180*** (0.052)	0.177*** (0.052)
Observations	5003	5003	5003	5003	5003
Counties	3000	3000	3000	3000	3000
Mean of DV	-0.0351	-0.0351	-0.0351	-0.0351	-0.0351
<b>Panel C: Controlling for 2012-2016 GOP swing quintiles</b>					
House × Retaliation exposure	-0.021* (0.011)	-0.025*** (0.008)	0.001 (0.013)	-0.023 (0.017)	-0.032 (0.020)
Senate × Retaliation exposure	-0.005 (0.007)	-0.002 (0.011)	0.007 (0.008)	-0.019*** (0.007)	-0.018*** (0.007)
Observations	5003	5003	5003	5003	5003
Counties	3000	3000	3000	3000	3000
Mean of DV	-0.0351	-0.0351	-0.0351	-0.0351	-0.0351

Notes: The independent variable is the change in the GOP vote share between 2018 and 2016 (or the most recent senate election to that) at the county level. All regressions control for election type fixed effects. Standard errors are clustered at the county level, stars indicate \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

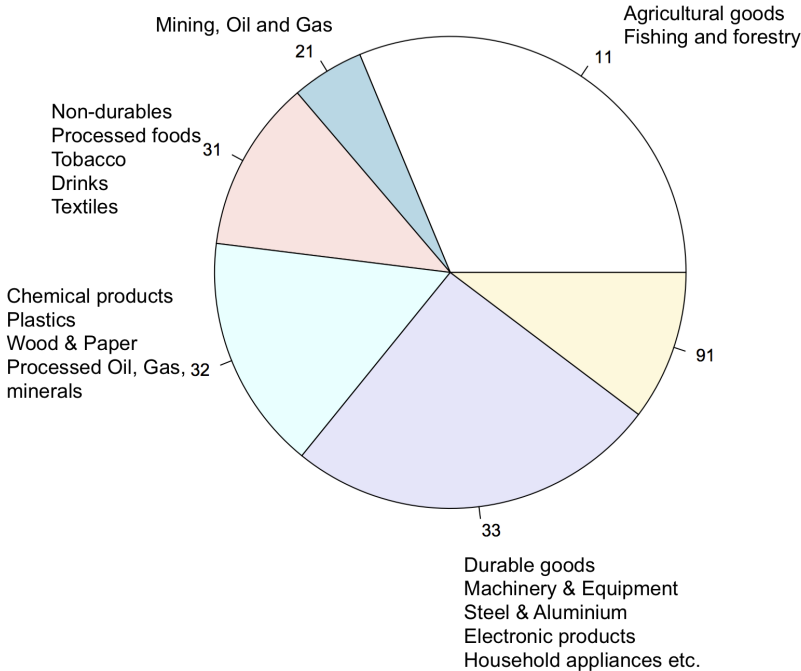
Table 6: Retaliation exposure and President Trump’s approval ratings

	(1)	(2)	(3)	(4)	(5)
		Retaliatory tariffs imposed by...			
	Combined	CN	EU	CA	MX
<i>Panel A: Overall</i>					
Post July 2018 × Retaliation exposure	-0.015* (0.008)	-0.046 (0.033)	-0.014 (0.010)	-0.010 (0.008)	-0.008 (0.013)
Retaliation exposure	0.056*** (0.009)	0.063*** (0.016)	0.043*** (0.010)	0.057*** (0.010)	0.055*** (0.008)
Observations	204577	204577	204577	204577	204577
Clusters	50	50	50	50	50
Mean of DV	.308	.308	.308	.308	.308
<i>Panel B: Democrats</i>					
Post July 2018 × Retaliation exposure	-0.025*** (0.009)	-0.048 (0.057)	-0.018*** (0.006)	-0.031** (0.012)	-0.031* (0.016)
Retaliation exposure	0.029*** (0.008)	0.059 (0.040)	0.018*** (0.004)	0.033*** (0.011)	0.036*** (0.009)
Observations	66079	66079	66079	66079	66079
Clusters	50	50	50	50	50
Mean of DV	.0511	.0511	.0511	.0511	.0511
<i>Panel C: Republicans</i>					
Post July 2018 × Retaliation exposure	-0.016 (0.015)	-0.066 (0.052)	-0.025** (0.011)	-0.010 (0.018)	-0.001 (0.030)
Retaliation exposure	0.045*** (0.013)	0.036*** (0.013)	0.029** (0.011)	0.049*** (0.014)	0.047*** (0.011)
Observations	63067	63067	63067	63067	63067
Clusters	50	50	50	50	50
Mean of DV	.819	.819	.819	.819	.819
<i>Panel D: Independents</i>					
Post July 2018 × Retaliation exposure	-0.014 (0.017)	-0.034 (0.075)	-0.015 (0.020)	0.006 (0.021)	0.007 (0.031)
Retaliation exposure	0.093*** (0.014)	0.098*** (0.031)	0.078*** (0.018)	0.092*** (0.014)	0.084*** (0.015)
Observations	75431	75431	75431	75431	75431
Clusters	50	50	50	50	50
Mean of DV	.291	.291	.291	.291	.291
State x Party x Education	x	x	x	x	x
Gender x Income Group	x	x	x	x	x
Age	x	x	x	x	x
Party x Time	x	x	x	x	x

Notes: The dependent variable is an indicator that takes the value 1 if a respondent indicates that they “approve of the way Donald Trump is handling his job as president”. Regressions are weighted by the county level measure of export jobs, standard errors are clustered at the state level with stars indicating \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .



Figure A2: Which sectors were targeted by retaliation measures? Combining the EU, Canada, Turkey, India, and Chinese retaliation lists.



**Notes:** Pie chart plots the trade-volume weighted distribution of countermeasures across sectors using the 2017 export volume.

Figure A3: Calculation of European Union rebalancing measures against steel tariffs taken from the EU's submission to WTO.

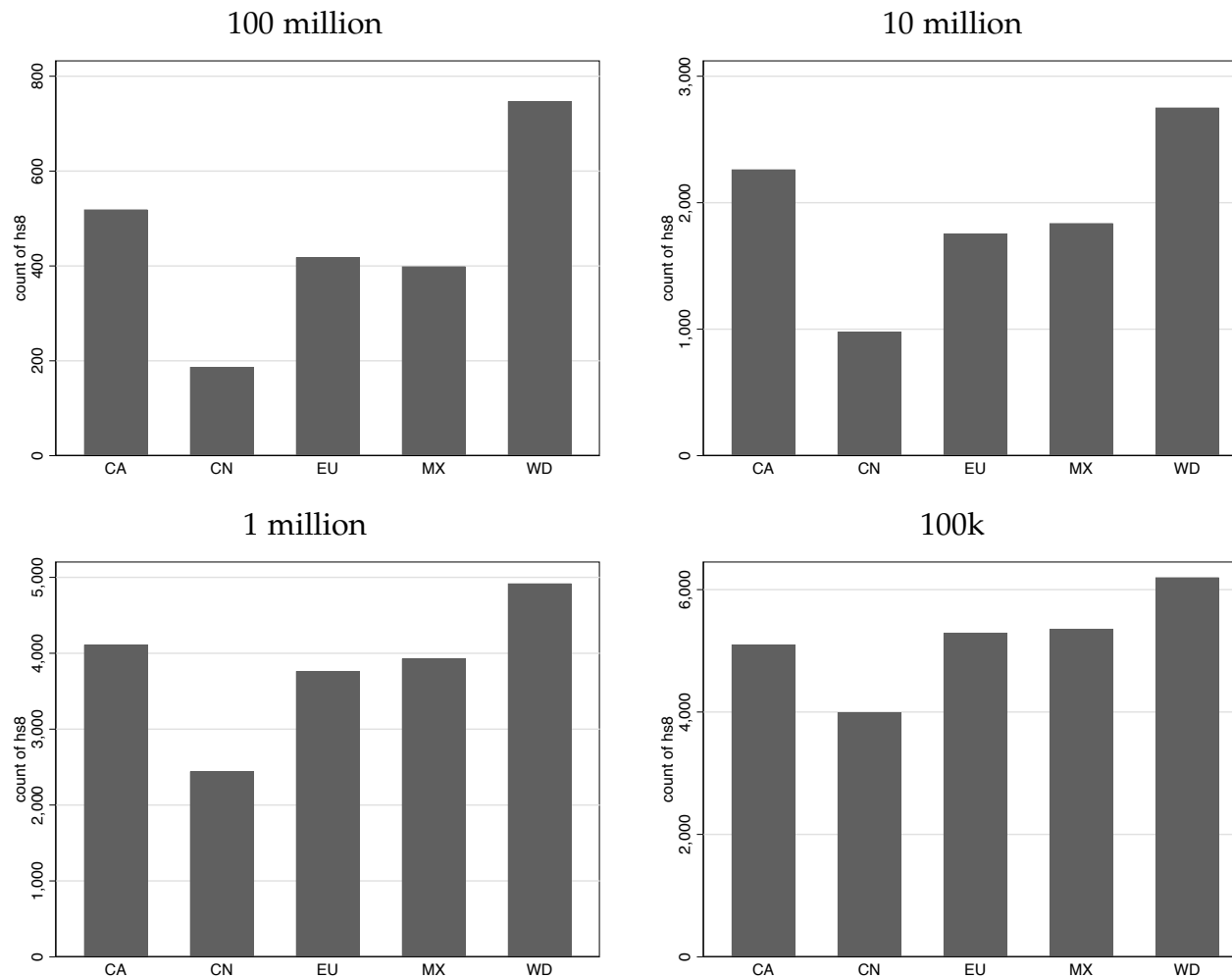
**Table 1**

<b>Products<sup>3</sup></b>	<b>2017 EU imports into the US</b>	<b>Additional US duty to EU imports into the US</b>	<b>2017 theoretical additional duty collected</b>
Flat carbon and alloy flat products	\$ 1.9 billion	25%	
Carbon and alloy long products	\$ 1.2 billion	25%	
Carbon and alloy pipe and tube products	\$ 1.2 billion	25%	
Carbon and alloy semi-finished products	\$ 0.09 billion	25%	
Stainless steel products	\$ 1.5 billion	25%	
<b>Total steel products</b>	<b>\$ 5.9 billion</b>	<b>25%</b>	<b>\$ 1.5 billion</b>
Unwrought aluminium	\$ 0.2 billion	10%	
Aluminium bars, rods and profiles	\$ 0.1 billion	10%	
Aluminium wire	\$ 0.1 billion	10%	
Aluminium plates, sheets and strip, of a thickness exceeding 0.2 mm	\$ 0.6 billion	10%	
Aluminium foil of a thickness not exceeding 0.2 mm	\$ 0.2 billion	10%	
Aluminium tubes and pipes	\$ 0.02 billion	10%	
Aluminium tubes and pipes fittings	\$ 0.001 billion	10%	
Castings	\$ 0.16 billion	10%	
Forgings	\$ 0.02 billion	10%	
<b>Total aluminium products</b>	<b>\$ 1.2 billion</b>	<b>10%</b>	<b>\$ 0.1 billion</b>
<b>Total</b>	<b>\$ 7.2 billion</b>		<b>\$ 1.6 billion</b>

Source: US ITC statistics

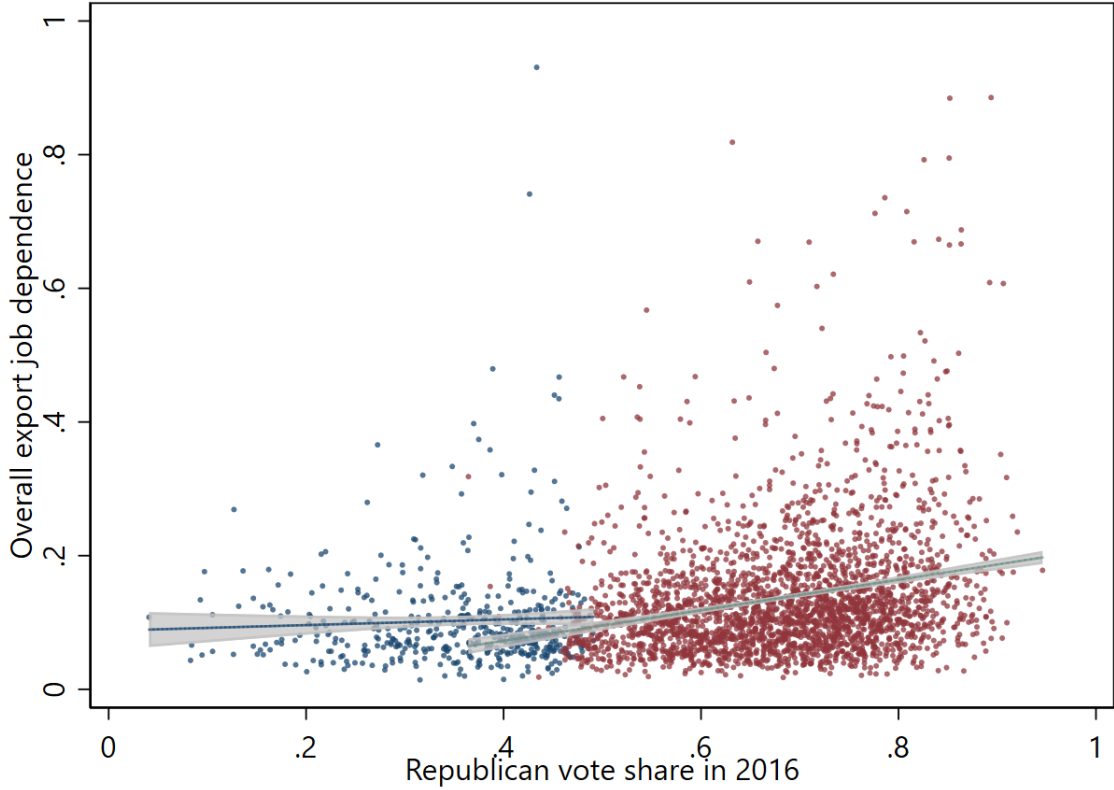
Figure A4: Potential set of commodities that could be chosen for retaliation: Number of HS8 codes where US exports are above certain size thresholds - in total the data includes 7193 unique HS8 codes

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**Notes:** Figure plots distribution of unique number of HS8 codes on which the US is exporting more than 100, 10, 1 and 0.1 million USD worth of goods in 2017. This is an indication as to how rich or unconstrained the retaliation response can be designed.

Figure A5: Export Job Dependence across counties and support for Republican party in 2016.

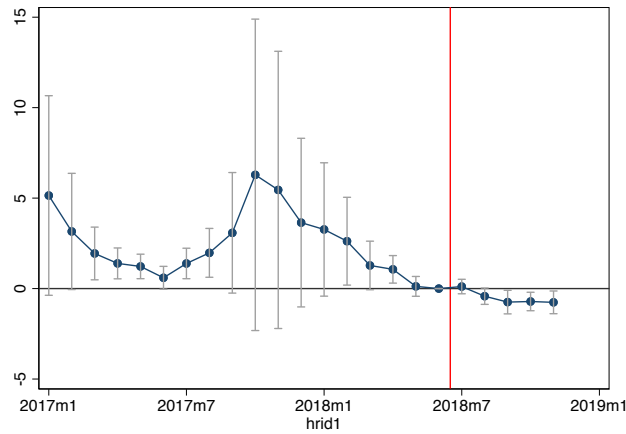


**Notes:** Figure plots the Republican party vote share in the 2016 Presidential election on the horizontal axis against the overall share of employment in a county that is reliant on exports.

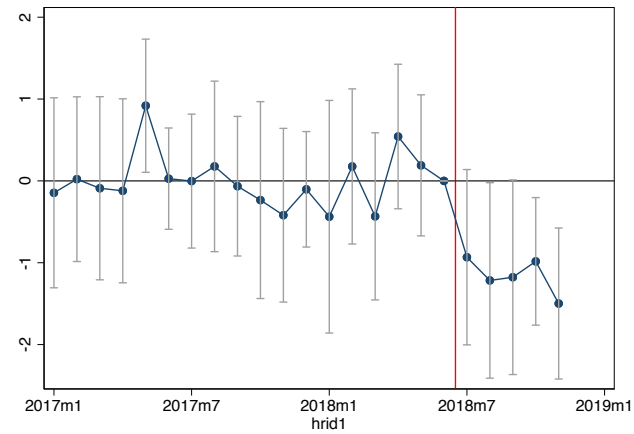


Figure A6: Impact of retaliation on US exports to retaliating country and the Rest of the World: pairwise event studies

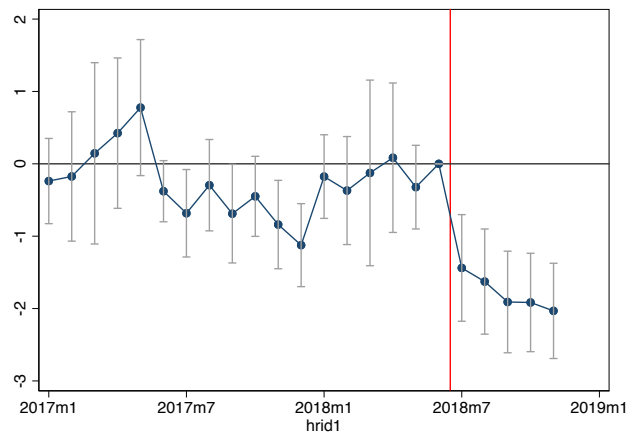
Panel A: China and ROW



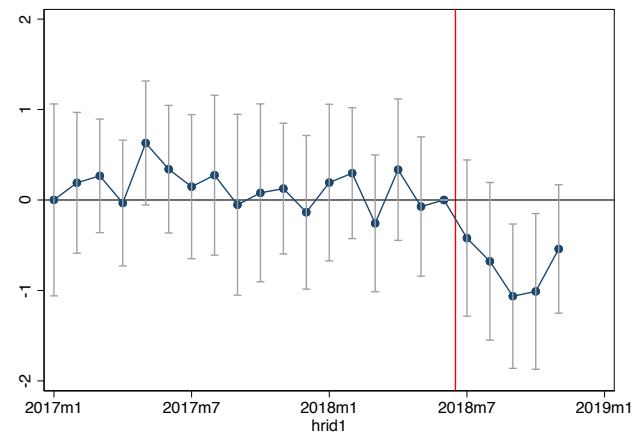
Panel B: EU and ROW



Panel C: Canada and ROW

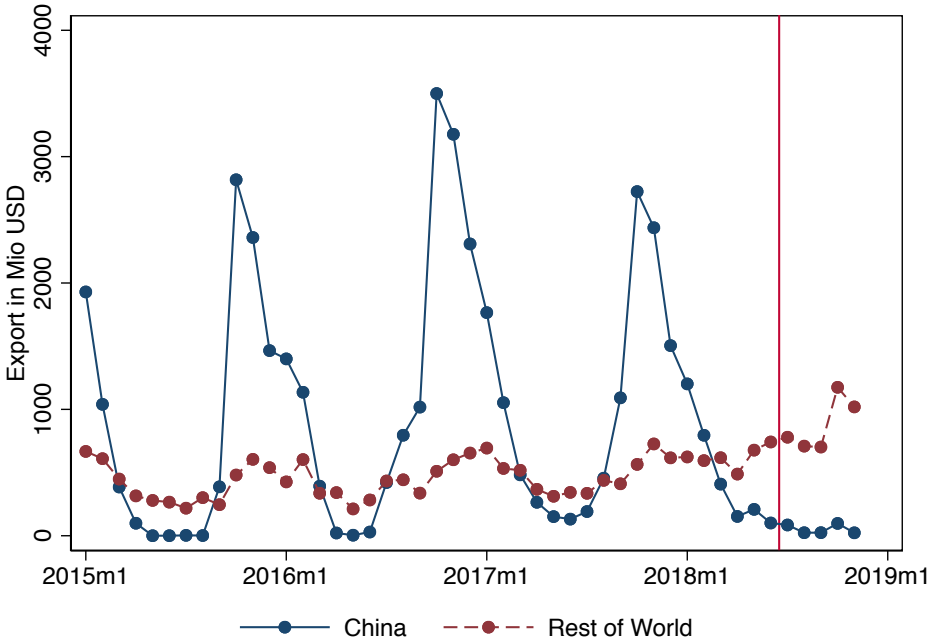


Panel D: Mexico and ROW



**Notes:** Figure plots estimates of the effect of retaliation exposure on trade between the US and the respective country vis-a-vis the rest of the world (not including China, Canada, Mexico and the EU). Estimates control for destination by HS8 good fixed effects and time effects. Standard errors are clustered at the HS4 level and 90% confidence bands are indicated.

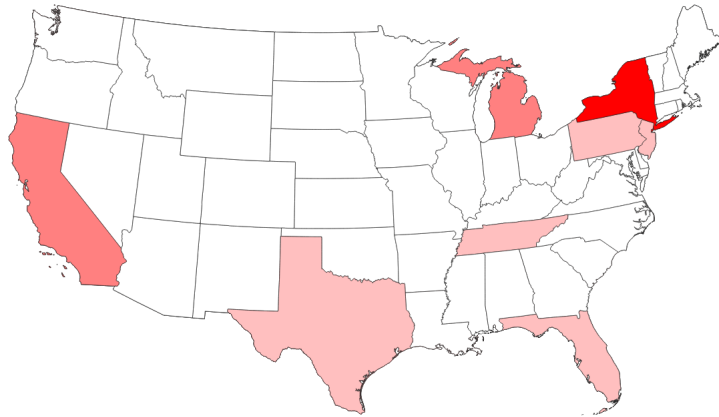
Figure A7: US Exports of Soybeans to China and the Rest of the World.



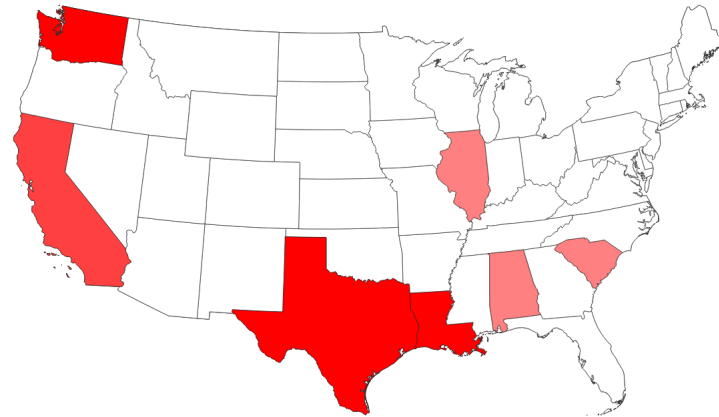
Notes: Figure plots the total exports from the US to China and the Rest of the World. Figures suggests that US exports are depressed overall with exports to the Rest of World not compensating for the fall in reduced exports to China.

Figure A8: Retaliation measures at the state level using the HS6 Origin of Export Movement data

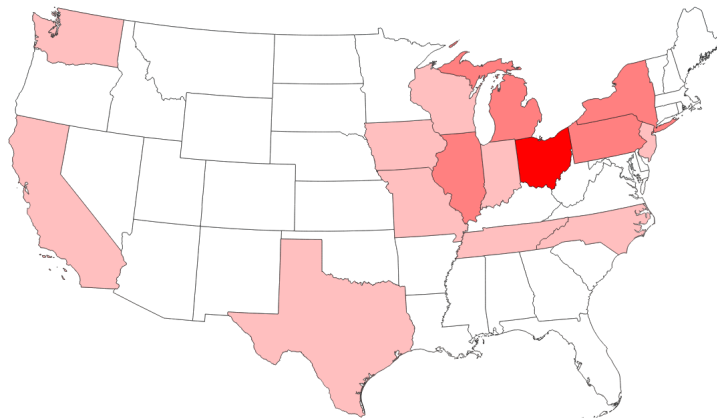
European Union



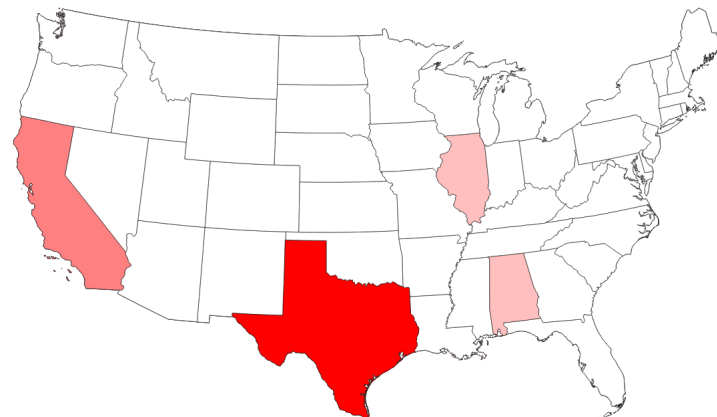
China



Canada



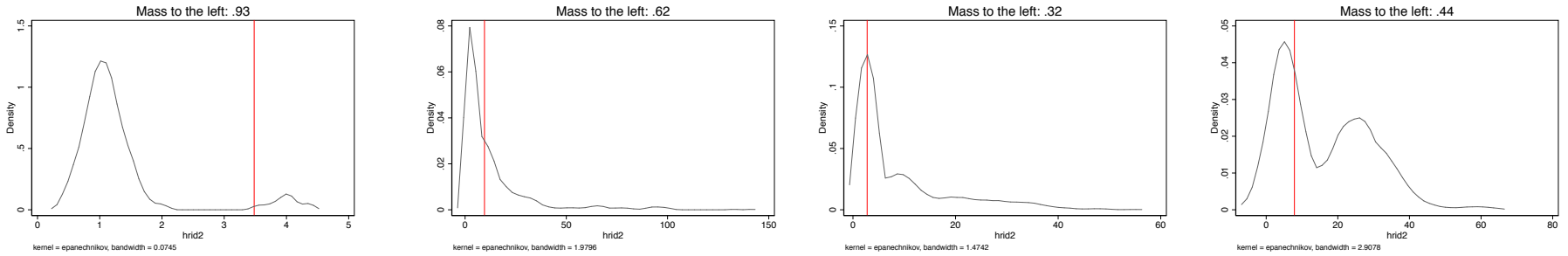
Mexico



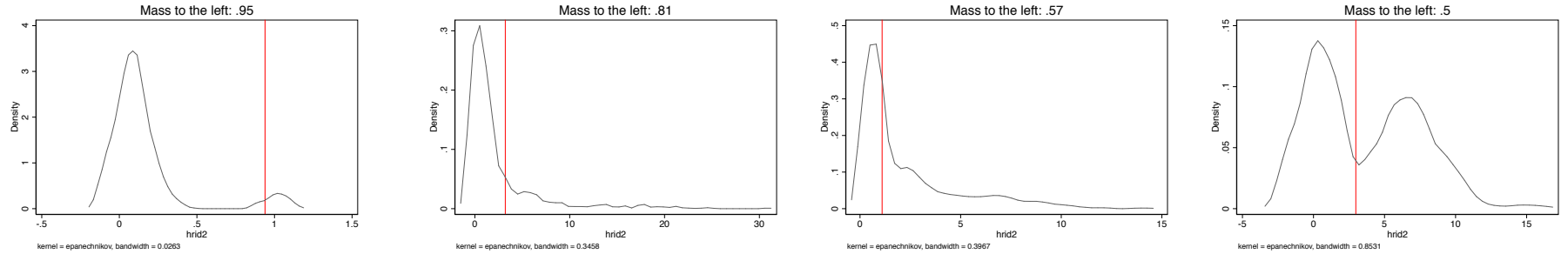
Notes:

Figure A9: Was retaliation targeted? Probabilistic simulation of alternative retaliation goods baskets and the resulting county level exposure measure.

Panel A: GOP vote share in 2016



Panel B:  $\Delta$ GOP vote share

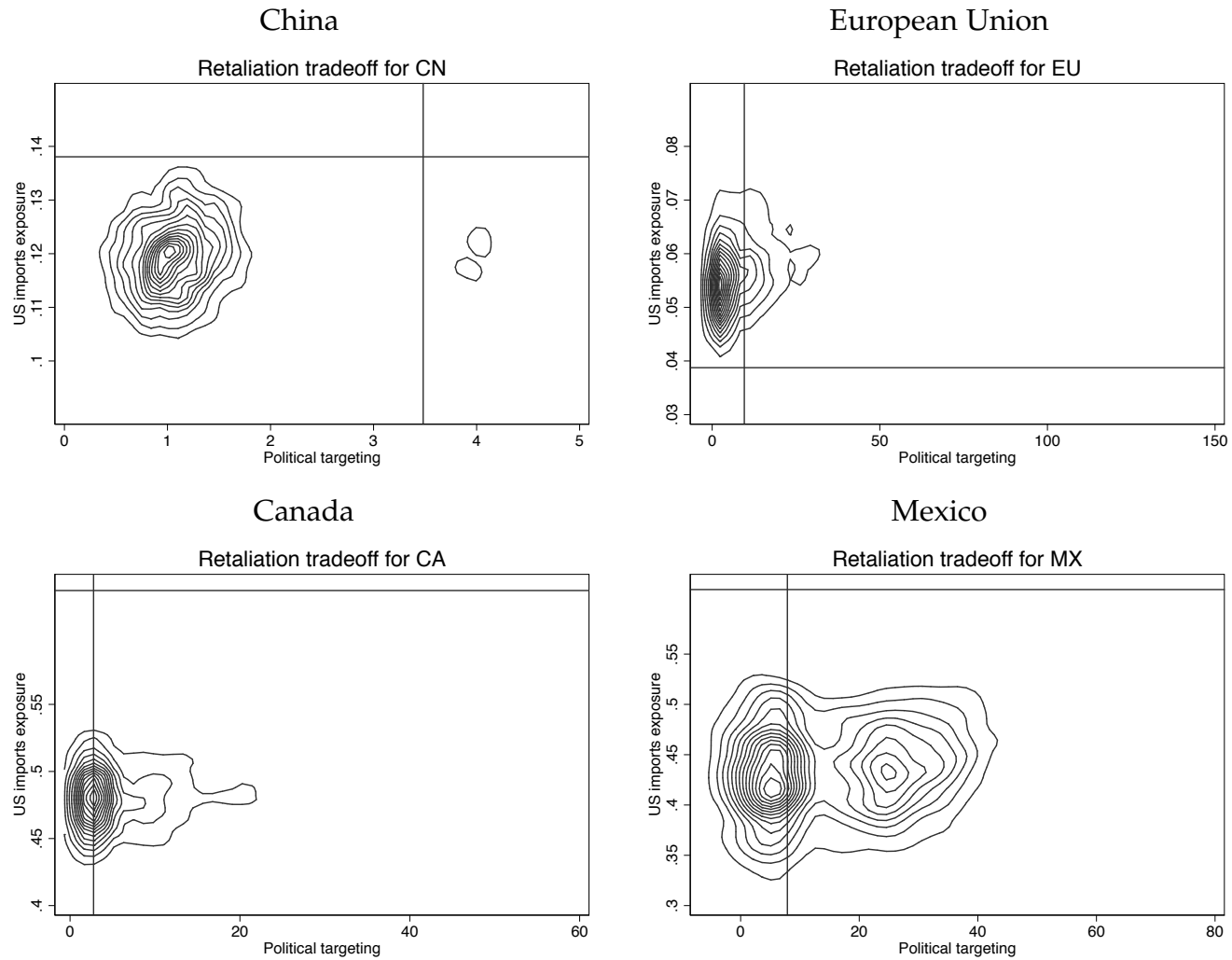


China European Union Canada Mexico

**Notes:** Figure plots kernel densities of the distribution of point estimates obtained from regressing the the GOP vote share in 2016 or the change in the GOP vote share between 2016 and 2012 on an indicator for 2018 interacted with a measure of the county's exposure to retaliatory tariffs from the EU (panel A) or China (panel B). The dataset is a county level panel covering 2016 and 2018 and the regressions control for county fixed effects and state by time fixed effects. Counties are weighted by the total number of export dependent jobs. The different point estimates are obtained from 100 alternative baskets of HS10 codes that China or the EU could have chosen to achieve a similar amount of rebalancing compared to the actual basket chosen. The effect of the actual basket is plotted as a vertical line.

Figure A10: Trade-off in political targeting and exposure to US imports: GOP vote share in 2016.

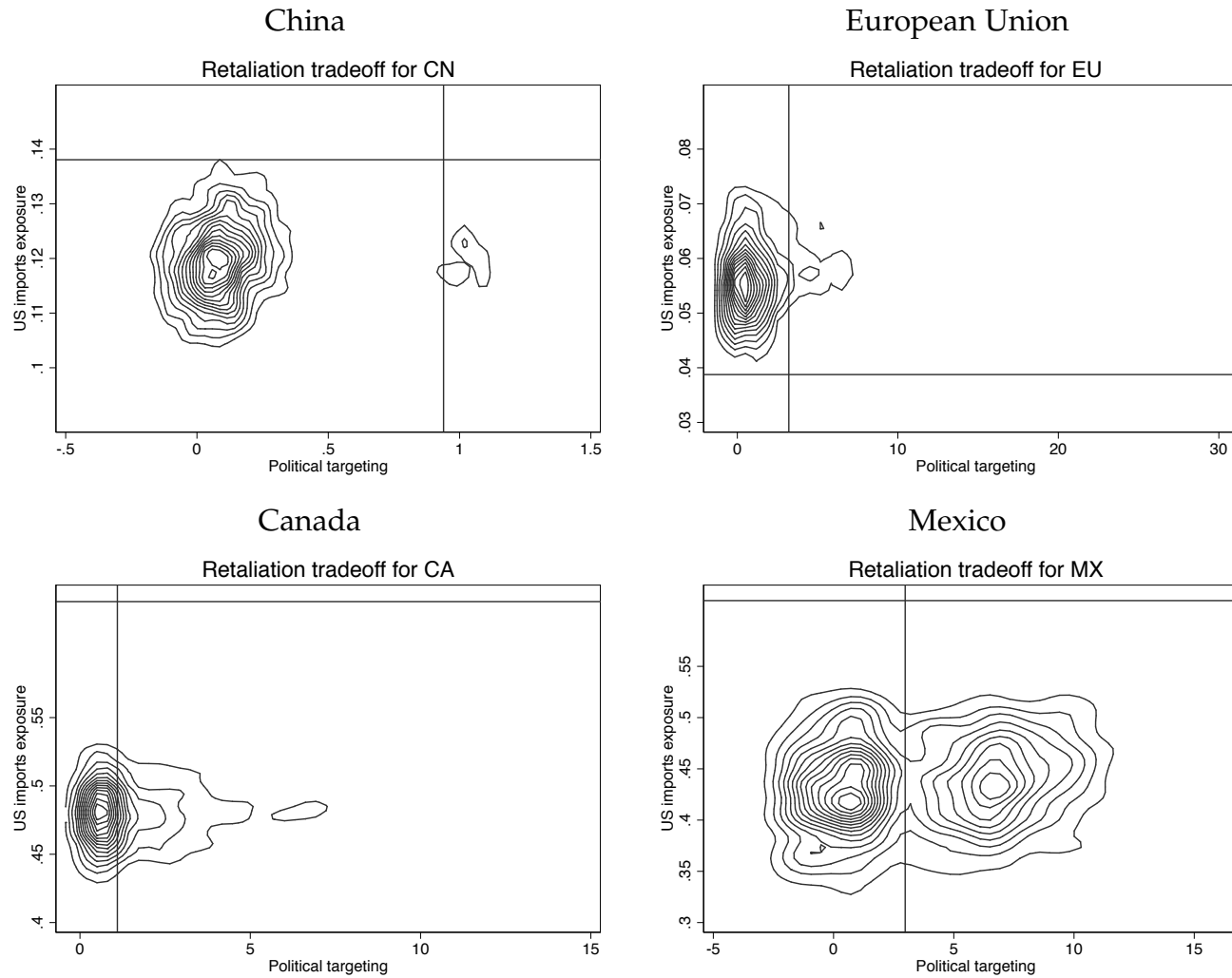
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**Notes:** Figure combines Panel A of Figure A9 and Figure 6 plotting kernel densities of the joint distribution the two measures across the 1000 simulated retaliation baskets. Areas in the lower right corner indicate high degrees of political targeting of an specific retaliation basket and a low degree of (potential) domestic economic harm. The implied values for the actual baskets are indicated as horizontal and vertical lines.

Figure A11: Trade-off in political targeting and exposure to US imports:  $\Delta$ GOP vote share 2012-2016.

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**Notes:** Figure combines Panel B of Figure A9 and Figure 6 plotting kernel densities of the joint distribution the two measures across the 1000 simulated retaliation baskets. Areas in the lower right corner indicate high degrees of political targeting of an specific retaliation basket and a low degree of (potential) domestic economic harm. The implied values for the actual baskets are indicated as horizontal and vertical lines.

Table A1: Robustness of degree of political targeting of retaliation measure studying GOP electoral performance in previous Presidential elections

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Combined			China			European Union			Canada			Mexico		
	2016	2012	2008	2016	2012	2008	2016	2012	2008	2016	2012	2008	2016	2012	2008
<b>Continuous tariff exposure</b>															
<i>Panel A: GOP vote share</i>															
Retaliation exposure	2.634***	1.850***	1.758***	3.483***	2.542***	2.356***	9.585***	6.377***	6.380***	2.767**	1.669	1.811*	7.883**	4.903*	5.119*
	(0.302)	(0.255)	(0.234)	(0.250)	(0.223)	(0.209)	(1.764)	(1.437)	(1.437)	(1.347)	(1.052)	(0.986)	(3.676)	(2.898)	(2.662)
Observations	3108	3109	3109	3108	3109	3109	3108	3109	3109	3108	3109	3109	3108	3109	3109
States	3108	3109	3109	3108	3109	3109	3108	3109	3109	3108	3109	3109	3108	3109	3109
Mean of DV	.426	.444	.432	.426	.444	.432	.426	.444	.432	.426	.444	.432	.426	.444	.432
<i>Panel B: Δ GOP vote share</i>															
Retaliation exposure	0.783***	0.092***	0.169***	0.939***	0.186***	0.210***	3.207***	-0.003	-0.063	1.098***	-0.142	0.280***	2.979***	-0.216	1.063***
	(0.071)	(0.034)	(0.038)	(0.071)	(0.029)	(0.047)	(0.485)	(0.221)	(0.253)	(0.317)	(0.091)	(0.106)	(0.834)	(0.269)	(0.250)
Observations	3108	3109	3032	3108	3109	3032	3108	3109	3032	3108	3109	3032	3108	3109	3032
States	3108	3109	3032	3108	3109	3032	3108	3109	3032	3108	3109	3032	3108	3109	3032
Mean of DV	-.0184	.0119	-.0545	-.0184	.0119	-.0545	-.0184	.0119	-.0545	-.0184	.0119	-.0545	-.0184	.0119	-.0545
<b>County in 10th decile of tariff exposure</b>															
<i>Panel C: GOP vote share</i>															
Retaliation exposure	0.117***	0.082***	0.080***	0.171***	0.120***	0.110***	0.081***	0.051***	0.050***	0.092***	0.064***	0.064***	0.103***	0.074***	0.073***
	(0.013)	(0.012)	(0.011)	(0.017)	(0.014)	(0.013)	(0.018)	(0.017)	(0.016)	(0.017)	(0.015)	(0.014)	(0.017)	(0.015)	(0.014)
Observations	3108	3109	3109	3108	3109	3109	3108	3109	3109	3108	3109	3109	3108	3109	3109
States	3108	3109	3109	3108	3109	3109	3108	3109	3109	3108	3109	3109	3108	3109	3109
Mean of DV	.426	.444	.432	.426	.444	.432	.426	.444	.432	.426	.444	.432	.426	.444	.432
<i>Panel D: Δ GOP vote share</i>															
Retaliation exposure	0.035***	0.002	0.009***	0.051***	0.010***	0.030***	0.031***	0.001	0.001	0.029***	-0.001	0.008**	0.029***	0.001	0.009**
	(0.004)	(0.002)	(0.002)	(0.005)	(0.002)	(0.003)	(0.006)	(0.003)	(0.003)	(0.005)	(0.003)	(0.004)	(0.005)	(0.003)	(0.004)
Observations	3108	3109	3032	3108	3109	3032	3108	3109	3032	3108	3109	3032	3108	3109	3032
States	3108	3109	3032	3108	3109	3032	3108	3109	3032	3108	3109	3032	3108	3109	3032
Mean of DV	-.0184	.0119	-.0545	-.0184	.0119	-.0545	-.0184	.0119	-.0545	-.0184	.0119	-.0545	-.0184	.0119	-.0545
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is either the republican vote share (Panel A and C) or the change in republican party vote share between consecutive presidential elections. The independent variable measures the county level retaliation exposure to retaliation from the countries or trading blocks indicated in the column heads. In Panel C and D, the measure is dummified to take a value 1 if a county level exposure measure is in the top decile. All regressions include state fixed effects. Counties are weighted by the 2016 number of jobs that depend on exports. Standard errors are clustered at the state level and are presented in parentheses, stars indicate \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Table A2: Robustness of degree of political targeting of retaliation measure studying GOP electoral performance in previous House elections

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Combined			China			European Union			Canada			Mexico		
	2016	2014	2012	2016	2014	2012	2016	2014	2012	2016	2014	2012	2016	2014	2012
<b>Continuous tariff exposure</b>															
<i>Panel A: GOP vote share</i>															
Retaliation exposure	2.458***	2.072***	2.048***	3.550***	2.712***	2.824***	8.809***	8.850***	7.345***	1.427	2.305	1.753	4.220	5.273	5.154
	(0.457)	(0.361)	(0.318)	(0.294)	(0.383)	(0.306)	(2.175)	(2.242)	(1.729)	(2.035)	(1.465)	(1.241)	(5.500)	(3.558)	(3.390)
Observations	3001	2999	3004	3001	2999	3004	3001	2999	3004	3001	2999	3004	3001	2999	3004
States	3001	2999	3004	3001	2999	3004	3001	2999	3004	3001	2999	3004	3001	2999	3004
Mean of DV	.454	.472	.448	.454	.472	.448	.454	.472	.448	.454	.472	.448	.454	.472	.448
<i>Panel B: Δ GOP vote share</i>															
Retaliation exposure	0.385*	0.023	0.188	0.837***	-0.116	0.315*	-0.052	1.513	0.232	-0.876	0.549	-0.163	-1.055	0.123	0.811
	(0.211)	(0.153)	(0.127)	(0.174)	(0.209)	(0.183)	(1.152)	(1.043)	(0.625)	(0.680)	(0.390)	(0.241)	(2.124)	(0.731)	(0.743)
Observations	2999	2999	2990	2999	2999	2999	2999	2999	2990	2999	2999	2990	2999	2999	2990
States	2999	2999	2990	2999	2999	2990	2999	2999	2990	2999	2999	2990	2999	2999	2990
Mean of DV	-.0182	.0244	-.0445	-.0182	.0244	-.0445	-.0182	.0244	-.0445	-.0182	.0244	-.0445	-.0182	.0244	-.0445
<b>County in 10th decile of tariff exposure</b>															
<i>Panel C: GOP vote share</i>															
Retaliation exposure	0.125***	0.105***	0.099***	0.147***	0.106***	0.116***	0.087***	0.072***	0.079***	0.086***	0.080***	0.073***	0.105***	0.077***	0.088***
	(0.018)	(0.016)	(0.015)	(0.024)	(0.019)	(0.019)	(0.026)	(0.022)	(0.019)	(0.027)	(0.023)	(0.022)	(0.027)	(0.022)	(0.021)
Observations	3001	2999	3004	3001	2999	3004	3001	2999	3004	3001	2999	3004	3001	2999	3004
States	3001	2999	3004	3001	2999	3004	3001	2999	3004	3001	2999	3004	3001	2999	3004
Mean of DV	.454	.472	.448	.454	.472	.448	.454	.472	.448	.454	.472	.448	.454	.472	.448
<i>Panel D: Δ GOP vote share</i>															
Retaliation exposure	0.020**	0.006	0.020***	0.041***	-0.010	0.037***	0.015	-0.007	0.014*	0.005	0.008	0.016	0.028*	-0.010	0.027**
	(0.010)	(0.009)	(0.007)	(0.010)	(0.011)	(0.010)	(0.016)	(0.012)	(0.007)	(0.014)	(0.014)	(0.011)	(0.016)	(0.014)	(0.012)
Observations	2999	2999	2990	2999	2999	2990	2999	2999	2990	2999	2999	2990	2999	2999	2990
States	2999	2999	2990	2999	2999	2990	2999	2999	2990	2999	2999	2990	2999	2999	2990
Mean of DV	-.0182	.0244	-.0445	-.0182	.0244	-.0445	-.0182	.0244	-.0445	-.0182	.0244	-.0445	-.0182	.0244	-.0445
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is either the republican vote share (Panel A and C) or the change in republican party vote share between consecutive presidential elections. The independent variable measures the county level retaliation exposure to retaliation from the countries or trading blocks indicated in the column heads. In Panel C and D, the measure is dummified to take a value 1 if a county level exposure measure is in the top decile. All regressions include state fixed effects. Counties are weighted by the 2016 number of jobs that depend on exports. Standard errors are clustered at the state level and are presented in parentheses, stars indicate \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .



## A Data Appendix

This section provides further details on the physics of natural gas shipping. It furthermore discusses and provides more details about the underlying data used in the empirical exercises.

### A.1 Retaliation product lists

For our analysis of the retaliatory measures, we collect the list of countermeasures that were published by the respective states or institutions using the Harmonized System (HS) codes:

1. EU proposed tariffs on US goods as countermeasures to the US steel tariffs were printed in the Official Journal of the European Union on the 17.5.2018, using Combined Nomenclature codes, the 8-digit CN code is identical with the HS codes for the first six digit (HS subheading). The list was accessed on 17.06.2018 at <http://trade.ec.europa.eu/doclib/press/index.cfm?id=1842>.
2. Chinese countermeasures to the US steel tariffs were circulated by the Chinese Ministry of Commerce on the 17/06/2018 with a second list circulated dated 08/08/2018, using full HS codes. The list was accessed on 08.08.2018 at <http://english.mofcom.gov.cn/article/newsrelease/significantnews/201806/20180602757681.shtml>.
3. Mexican proposed countermeasures to the US steel tariffs were printed in the Mexican DOF - Diario Oficial de la Federacion on the 05/06/2018, using full HS codes. The list was accessed at [http://www.dof.gob.mx/nota\\_detalle.php?codigo=5525036&fecha=05/06/2018](http://www.dof.gob.mx/nota_detalle.php?codigo=5525036&fecha=05/06/2018), accessed 17.06.2018.
4. Canadian countermeasures to the US steel tariffs were printed by the Canadian Department of Finance, using four digit and full HS codes. The list was accessed at <https://www.fin.gc.ca/activty/consult/cacsap-cmpcaa-eng.asp>, accessed 17.06.2018.

## A.2 Extended description of Brookings Export Monitor

The Brookings (2017) Export Monitor constructs a measure of county-level exports at coarse set of 131 NAICS industries. The data combines various data sources, including the USA Trade Online (Census) for goods exports, the Bureau of Economic Analysis (BEA) for services exports, the Internal Revenue Service (IRS) for royalties data along with Moody's Analytics production estimates at the county level, and university level foreign students' expenditures from NAFSA.

The resulting database estimates exports of goods and services for each of the 3113 counties in the 50 states plus the District of Columbia. The estimation technique allocates U.S. exports for a given industry to each county based on their share of national production in that particular industry. This approach assumes that if Los Angeles County produces 5 percent of the national value-added of computer manufacturing, then this county also exports 5 percent of U.S. computer and electronics. The data is aggregated afterwards at metropolitan, state, region, and national level.

An alternative approach would be to use U.S. exports reported by origin-of-movement, which is available from Census at the state by six digit goods level. The important caveat with this approach is that the export origin of movement does not reflect the actual physical origin of the good. This effect is particularly noticeable for agricultural shipments. For these shipments intermediaries located in inland states are shipping agricultural commodities down the Mississippi River for export from the port of New Orleans. In this case, the state reflects Louisiana, the state where the port of New Orleans is located, as the state of origin of movement. The states in which the commodities were grown and originally shipped are lost.<sup>15</sup>

This problem is particularly evident when studying the distribution of retaliation across US states in Appendix Figure A8. The figure highlights that, especially for China and the European Union, the incidence of the retaliation measures, once allocated by the HS6 origin of movement export data is strongly concentrated in the coastal states, which are unlikely to represent the origin of production. Hence,

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<sup>15</sup>See <https://www.census.gov/foreign-trade/aip/elom.html>.

our approach using production data is better suited to measure the geographic incidence.

The Export monitor provides, for each county  $c$  a measure of exports in industry  $i$ ,  $X_{c,i}$ . In addition, the data also provides for an estimate of the total exports at the county level and the number of export dependent jobs. The latter will be used to weight the regressions.