Section 301 and Politics: Analysis of Tariff Exclusions*

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Abstract

The Trump Administration imposed tariffs on Chinese imports starting in 2018. American firms who rely on Chinese imports were allowed to apply for exclusions for products. In this paper, we investigate political factors affecting the approval rates for these tariff exclusions. We find that tariff exclusion is increasing in the Republican vote share. Counties with a 10 percentage point higher Republican vote share experience a 10% higher probability of tariff exclusion approval. We consider factors affecting this estimate such as firm selection into requesting and legitimacy of request.

JEL Classification: F13, F14, D73
Keywords: International Trade, Political Economy

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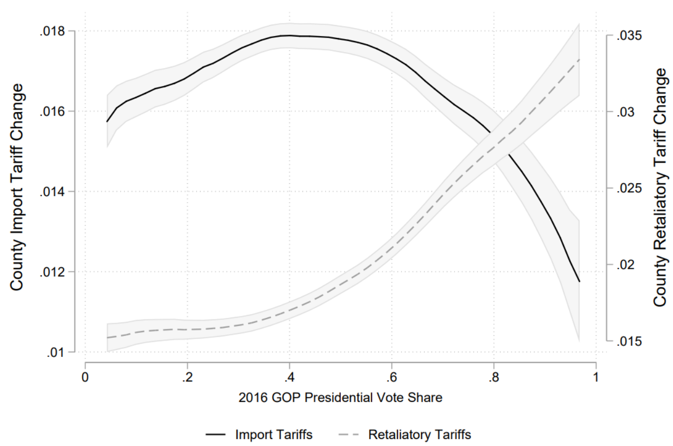
1 Introduction

Recent United States protectionist trade policies and subsequent retaliations show political motivations. The Trump administration began imposing a series of Section 301 tariffs on China in 2018. Intentions ranged from lowering trade deficit and increasing manufacturing jobs to state goals of more favorable trading, intellectual property, and foreign relations. Despite these intentions, evidence shows that the US trade war and subsequent retaliation are politically motivated. Fajgelbaum et al. (2020) find that politics matter in the decisions of these tariffs. In Figure 1, they find politically-mixed areas receive the largest degree of protection from import tariffs (solid line), while the Republican areas experienced more harm from retaliatory tariffs (dashed line). Fetzer and Schwarz (2021) extend this analysis to China specific retaliation and provides evidence that the retaliation is targeted against the core Republican voter base.

Figure 1: Tariff Changes vs. 2016 Republican Vote Share



Notes: Figure taken directly from Fajgelbaum et al. (2020) Figure VII.

In our paper we focus on another aspect of the trade war, a United States Trade Representative (USTR) led exclusion process from the additional Section 301 import tariffs on certain Chinese goods. While increases in tariffs, ranging from 10-25%, were imposed on approximately $463 billion worth of imports of Chinese goods, more than $71 billion were subsequently excluded through this exclusion process (U.S. Government Accountability Office, 2021).

Interested in the political motivation of the administration, we ask whether the exclusion process from the import tariffs on Chinese goods has a political bias. The Office of the United State Trade Representative (USTR) had authority over the appeals for tariff exclusions, and the head of the USTR is a direct political appointee of the US President. In a procedural document, the USTR reported to have "applied their judgement" in making key decisions, such as what was considered a tariff causing "severe economic harm" to a firm, the main reason for denial of exclusion requests (U.S. Government Accountability Office, 2021). In their July report, the U.S. Government Accountability Office concluded that without "fully documented internal procedures, USTR lacks reasonable assurance it conducted its reviews consistently." The conglomeration of the political nature of the USTR and lack of consistencies in the process, leads us to hypothesize that partisan politics may matter in the approval decision of an exclusion request.

More specifically, this paper investigates the political party's influence on approval decisions for tariff exclusions. We examine how the political party makeup of a county can affect the approval rates for tariff exclusions. Using the county share of votes for Trump, the Republican candidate during the 2016 presidential elections and subsequent US President during the exclusion process, we examine the outcomes of exclusion requests on Chinese imports from the Section 301 tariffs.

Theories on the targeting of policies and allocation of resources to areas of certain political representation stem from two main lines of thought within political science and political economy. One in which the party in charge targets areas that are politically mixed, attempting to maximize party reelection probability (Lindbeck and Weibull, 1987) (Lindbeck and Weibull, 1993). The alternative hypothesis is that where the party in power reward voters in areas of larger support (Cox and McCubbins, 1986) as it is a less risky investment.

Our empirical analysis attempts to provide evidence for or against either one of these theories. We do not find any support for higher approval rates in politically mixed counties. However, we do find robust evidence for a higher Republican share leading to a higher probability of exclusion approval. This is consistent with theory of policies targeted to benefit the base of the president, similar to Cox and McCubbins (1986). We find that counties with a 10 percentage point higher Republican vote share experience a 10% higher probability of tariff exclusion approval.

There are two additional effects that may complicate our story: 1) if there was an expectation of bias in the process and thus inducing a nonrandom selection of certain firms into applying; and 2) if requests either from Republican or Democrat areas were of different quality.

Our theoretical framework presented in Section 5 provides us with conditions in which our estimates are an underestimate or overestimate. We believe, however cannot definitively prove that the bias after accounting for all our controls is underestimated. Our empirical methodologies we explain in Section 6 control for potential of differences in legitimacy of applications through various level of product and firm controls and fixed effects.

The paper proceeds as follows. Section 2 reviews past literature and puts this paper in context. Section 3 describes the institutional background of the Section 301 and the exclusion process. Section 4 covers the collection of the data and the summary of the data used. Section 5 lays out a theoretical framework in which we use to help interpret our empirical results. Section 6 lays out our empirical methodology and identification approach. Section 7 summarizes our results. Finally, Section 8 we conclude with a discussion of future research.

2 Related Literature

The Trump administration has pursued a protectionist trade policy in order to increase employment in the manufacturing industry. In line with this platform, Trump has increased trade protection against China because manufacturing companies took advantage of its cheap labor and became a prominent exporter of manufacturing goods. As a result of Chinese import competition and firm relocation to China, the US manufacturing industry suffered significant job losses. Autor et al. (2013) analyzed the effect of rising Chinese import competition between 1990 and 2007 on US local labor markets. They find that these labor markets experienced increased unemployment, decreased labor force participation, and lower wages.

Targeting China, the Trump administration started an investigation regarding discriminatory business practices against US firms in 2017, imposing Section 301 tariffs as a result. However, US firms who rely on Chinese imports are then burdened by these tariffs. Recent literature estimates significant losses for US firms and consumers as a result of these tariffs on Chinese imports. For example, Amiti et al. (2019) claims that tariffs on Chinese imports are costing US consumers and firms an additional \$3.2 billion per month in added costs, while Fajgelbaum et al. (2020) estimates that, accounting for tariff revenue and domestic producer gains, these tariffs resulted in an aggregate real income loss of \$7.2 billion or 0.04% of US GDP in 2018. Carvalho et al. (2019) conducts a welfare analysis and finds that the tariff increases (during the \$50 billion round) resulted in a welfare decrease from \$19.3 to \$23.6 billion for the US.

To alleviate this burden on US firms, the USTR has allowed US firms to appeal for tariff exclusions. These appeals are decided by the USTR. Since the USTR is appointed by the US President, we examine the potential political bias for increased approval rates in counties with higher Republican vote share.

Previous research has shown evidence on using bureaucratic connections through elected officials for favorable enforcement outcomes. Young et al. (2001) finds that there is a considerably lower fraction of audited tax return in IRS districts that house key representatives on congressional committees. Correia (2014) claims that politically connected firms are less likely to be investigated by the SEC, and if they are prosecuted, these politically connected firms face lower penalties. Gulen and Myers (2017) documents significantly lower rates of violation of the Clean Water Act in battleground (swing) states. Heitz et al. (2019) finds evidence that firms that are more politically connected (defined as having donated to victors in elections) realize less regulatory enforcement and fines from the EPA Clean Air Act.

Our paper adds to this literature on favorable policy outcomes by showing the existence of a relationship between the 2016 county voting patterns and the probability of a tariff exclusion approval. We also contribute to the literature that evaluates the heterogenous regional impacts of the Section 301 tariffs in the United States. Fajgelbaum et al. (2020) finds that it was the politically mixed counties that received the most protection during the trade war. Robinson et al. (2019) provides evidence that the US-China trade was harmful not only to the involved countries but also created trade diversion in other markets. Amiti et al. (2019) finds that the impact of tariff spikes has been almost completely passed through to the prices on the imported goods that were affected by this conflict. However, it does not find any changes to the terms-of-trade. Similar results are found by Flaaen and Pierce (2019) for the manufacturing sector.

While some papers have evaluated the effect of the Section 301 tariffs (Amiti et al. (2020), Amiti et al. (2019), Fajgelbaum et al. (2020), Robinson et al. (2019), Flaaen and Pierce (2019)), to our knowledge we are the first academic paper to investigate this exclusion process or any part of the procedure leading to the finalization of the tariff list.

3 Institutional Background

A USTR investigation in 2017 found China's trade practices unfair and harmful to the United States.[1]

1. China uses foreign ownership restrictions, such as joint venture requirements and foreign equity limitations, and various administrative review and licensing processes, to require or pressure technology transfer from U.S. companies.

2. China's regime of technology regulations forces U.S. companies seeking to license technologies to Chinese entities to do so on non-market based terms that favor Chinese recipients.

3. China directs and unfairly facilitates the systematic investment in, and acquisition of, U.S. companies and assets by Chinese companies to obtain cutting-edge technologies and intellectual property and generate the transfer of technology to Chinese companies.

4. China conducts and supports unauthorized intrusions into, and theft from, the computer networks of U.S. companies to access their sensitive commercial information and trade secrets.

The US thus implemented tariffs on $34 billion worth of Chinese exports in hope of pressuring China to change these practices. An escalation of tariffs both on the US and Chinese sides followed. US subsequently implemented an additional 3 rounds of tariffs on $16, $200, and $300 billion worth of goods. The final list of tariffs were split into 2 sections, 4A and 4B, List 4B was never implemented as part of ongoing trade negotiations.

Around the announcement of the first round of tariffs, stakeholders raised concerns that specific firms may be severely harmed if goods were only available from China. Hence after the imposition of list 1 of these tariffs, the USTR began a process to allow individuals or firms to file for specific products to be excluded from these tariffs for a certain time, in most cases a year.

Both the tariff lists and the exclusion lists were made utilizing the Harmonized Tariff Schedule of the United States (HTSUS). This is a hierarchical classification system where the number of digits is related to the specificity of the good. For example

[1] See Federal Register Vol. 83, No. 67, pg 14907 for details.

After a review period the USTR began to release exclusions on certain products varying in specificity. Some examples of these exclusions are:

> (9) Inflatable boats, other than kayaks and canoes, with over 20 gauge polyvinyl chloride (PVC), each valued at $500 or less and weighing not over 52 kg (described in statistical reporting number 8903.10.0060)[2]
>
> (33) Tuners designed to clip onto musical instruments and indicate whether the instrument is in tune (described in statistical reporting number 9031.80.8085)[3]
>
> (74) Battery-powered timers, with clock or watch movements, with opto-electronic display only, incorporating a 360-degree rotating timer control, a start/stop control, a reset control, and an audible alarm, with a maximum time count of 9 hours, 59 minutes, and 59 seconds (described in statistical reporting number 9106.90.5510) [4]

This procedure was set in place after the second wave of tariffs was proposed. The USTR processes requests on a case by case basis, however the process leaves much to discretion. Some of the things that they look into are availability of the product from a non-Chinese source, previous attempts to source the product from another source, economic harm the tariff imposes on the specific importer, and how important the tariff is to China's industrial programs.

U.S. Government Accountability Office (2021) concluded that without "fully documented internal procedures, USTR lacks reasonable assurance it conducted its reviews consistently." They additionally found that of denied, 69% were do to failure to show severe economic harm and 23% were due to failure to show the product was only available from China. For showing severe economic harm, USTR reviewed explanation the requester provided as well as other information provided by the requester regarding imports and business size. However "USTR officials said they did not specifically define what they meant by 'severe economic harm.' Instead, they applied their judgement by considering the size of the requesting company's operations, level of imports, and ability to absorb the tariffs." For availability outside of China, if firms failed to show this, then the USTR "considered denying the request."

In whole, the USTR "examined the totality of evidence" when granting or denying a request and that "no one factor was essential." A request may have been granted even if it was strategically important to China's industrial programs if it were to cause severe economic harm to a firm, however, severe economic harm was not well defined.

[2]Federal Register August 7, 2019 pg 38718
[3]Federal Register March 25, 2019 pg 11157
[4]Federal Register Oct 28, 2019 pg 57807

4 Data

Our main source of data is the registry of tariff exclusion requests and approvals. We obtain information on product codes (Harmonized Tariff System of the United State (HTSUS) standard at the 10-digit level), industry classification (Broad Economic Category (BEC)) codes, company name, and the stage of the exclusion process: granted, denied, or pending for Waves 1-3. The data is assembled by the open source group *QuantGov*, organized by the Mercatus Center at George Mason University.

Since the data from *QuantGov* did not include information for exclusion wave 4a, we web-scrape the USTR exclusion request portal, utilizing the R packages *Rselenium* and *rvest* to gather information such as HTS code, requester's name, product description, and exclusion decision.[5] We then clean this data to be consistent with our main source and merge it with the data from Mercatus.

The Harmonized Tariff System of the United States (HTSUS) is a hierarchical classification system where more digits imply higher level of product detail. For example 3919101010 is defined as "Plastics and articles thereof; Rubber and articles thereof: Self-adhesive plates, sheets, film, foil, tape, strip and other flat shapes, of plastics, whether or not in rolls: In rolls of a width not exceeding 20 cm: Having a light-reflecting surface produced in whole or in part by glass grains (ballotini): Pavement marking tape" Each colon denotes an additional 2 digits of specificity in the HTSUS code 3919101010. So this product belongs to the 2-digit HS Chapter 39: "Plastics and articles thereof; Rubber and articles thereof" but then also belongs to the groups 3919, 391919, and 39191010 which are defined as HTS-4, HTS-6, and HTS-8 codes, respectively.

We then further supplement this core data with firm characteristics from *Orbis*, product characteristics from various sources, and county characteristics.

To create variables on product characteristics, we use concordance files available from the Census website to map each HTSUS 10-digit code into other product classification systems[6]: Standard Industrial Classification (SIC), North American Industry Classification System (NAICS), and Bureau of Economic Analysis' principal end-use classification.

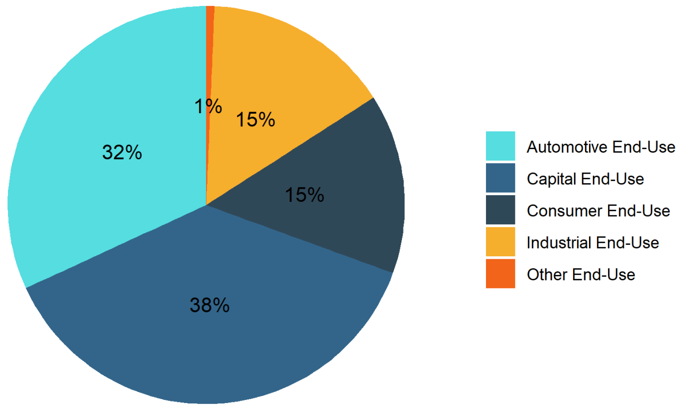
The end-use classification allows us to group goods six principal categories as defined as the Bureau of Economic Analysis. These groups are: (1) Foods, Feeds, & Beverages, (2) Industrial Supplies, (3) Capital Goods, (4) Automotive Vehicles, etc., (5) Consumer Goods, and (6) Other Goods. We follow U.S. Government Accountability Office (2021) in grouping agricultural and other goods together as one group, yet this category only accounts for less than 1% of the observed exclusion requests. The breakdown of the end-use classification by request is reported in Figure 2.[7]

[5] Code for this can be found on jmwestenberg's GitHub.

[6] The concordance we utilize can be found on Census' Website by clicking here.

[7] More detail on the breakdowns of what goods are included within groups can be found here.

Figure 2: Fraction of Primary End Use - By Request



Additionally, the Census classifies goods of advanced technology. Products that are goods related to biotechnology, life sciences, opto-electronics, information & communications, electronics, flexible manufacturing, advanced materials, aerospace, weapons, or nuclear technology. We simply create a dummy if a certain HTSUS code falls within a high technology classification. Within our data, approximately 3.5% of requests are made for goods of Census' classification of advanced technology.

The USITC released a list of imported goods that were important for public health's response to the COVID-19 pandemic. As exclusions for these emergency products were granted during the time of the pandemic, we create an indicator variable to control for the unexpected variation from the list of public-health related goods. Products within this classification only accounted for approximately 1% of the requests in our dataset.

Using our mapping into NAICS codes, we utilize County Business Patterns Data to control for US-level employment within NAICS category. County Business Patterns is a dataset created by Census on a yearly basis which includes total Mid-March Employment by a 6-digit NAICS Code. We report the distributional statistics on this variable in Table 1.

We use Census' US Trade Online data to gather information about imports by HTSUS 10-digit code, specifically, dollar value of imports from the rest of the world and dollar value of imports from China to calculate the share of Chinese imports by product. The descriptive statistics for this variable can be found in Table 1 below.

To control for firm-specific variation and to find information on petitioning firms' locations, we searched Orbis database. The matching procedure used by Orbis rates the potential matches[8] and allows the user to review variables specific to each firm, including firm location. While the latter is our primary variable of interest, we also gather two other variables to proxy for firm size: number of employees employed and operating revenue turnover. The mapping of firms into counties results in over 500 counties being represented in our dataset. Summary of their charaterictics is presented in Table 1.

[8]We take Orbis' best match on the firm name.

Table 1: Summary Statistics for Control Variables

Variable	Average	Standard Deviation	Min	Max
Industry Employment (Thousands)	47.4	467.7	0.2	381.4
China's Share of Imports	0.338	0.255	0	1
Value of Imports (Bil USD)	1.07	1.90	~ 0	23.39
Firm Employees (Thousands)	2.07	11.70	~ 0	164
Firm Oper Rev Turn (Mil USD)	0.98	9.40	~ 0	260.17

Note: Summary statistics are for the final sample after matching with all datasets. ~ 0 is reported instead of zero to differentiate rounded zeros from true zeros.

Using the city and state names from the Orbis data, we implement a two-step procedure to map the firm locations into a county level Republican vote share for the 2016 presidential election. First, we used the United States Cities Database (from simplemaps.com) to map each firm's city and state locations to their corresponding counties. Next, we match the counties in our data set with the their corresponding Presidential Election Returns (from the MIT Election Lab). We then calculate the share of the votes that the Republican candidate (Donald Trump in 2016 and Mitt Romney in 2012) received. We plot the Republican vote share by county for 2016 in Figure 9 and 2012 in Figure 10.

We understand the importance of local economic conditions, and include 2017 county unemployment rates from the Bureau of Labor Statistics data as a control variables (Figure 12 in Appendix A). We believe that each company's policy is determined by their respective headquarters, which, in turn, is the most likely entity to file the exclusion requests. Since there is substantial variation in voting patterns even within the state, we assume that county-level observations would capture this variation.

5 Model Framework

While our empirical framework controls for potential differences in legitimacy coming from Republican versus Democratic areas, we cannot ignore the fact that if there was bias expected in the exclusion decision process this could result in the marginal legitimacy of applications coming from Republican or Democrat areas to be different. As we do not have data on potential applications, we turn to a simple model to form expectations for the results of our empirical analyses. We aim to address under what conditions our estimates could be biased and the direction of the bias given firms expectations.

5.1 Basic Framework

The potential value of an exclusion request to a firm and the legitimacy of the request are intrinsically linked. Conditional on firm size, if an exclusion from an import tariff would be of high value to a firm, then the firm would have a legitimate case that this import tariff severely harmed their business. While if an exclusion request from a tariff would have near zero value to a firm, then that firm would not really be hurting from that tariff, thus not having a very legitimate request for exclusion.

Suppose that any potential request for a firm i has a value $v_i \in [0, \bar{v}]$. Then we can define the legitimacy of the application as the normalization of v_i that lies between 0 and 1, that is $l_i = \frac{v_i}{\bar{v}} \in [0,1]$. Moreover, assume that firms have a fixed cost c of filing an application. We will also normalize this, so $c = \frac{FC}{\bar{v}}$.

Consider now that there is an agency handling the requests. Let's assume that the agency has a threshold that is known internally but is not precisely known by the firms. We relate this to the USTR's condition of severe economic harm, which was likely the main consideration in the decision process of an application. Let's refer to the agencies internal threshold as $\bar{\tau} \in [0,1]$ where they approve a requests with $l_i \geq \bar{\tau}$ and decline a request with $l_i < \bar{\tau}$.

Since firms do not know the exact $\bar{\tau}$, they have some distributional expectations of it, $F(\tau)$. Under this condition firms would file a request if and only if $l_i \geq \mathbb{E}(\tau) + c$. Since $\bar{\tau}$ is related to the USTR's approval threshold, this uncertainty is related to the fact that while conditions for approval were made known in a very broad sense, the USTR did not define specifics on what requests would be approved and which ones would be denied.

Now assume that $F(\tau)$, the firm's distributional expectations of $\bar{\tau}$, follows $F(\tau) = \hat{\tau} + \varepsilon$, where $\varepsilon \sim \mathbb{U}[-\frac{1}{2\zeta}, \frac{1}{2\zeta}]$ and $\hat{\tau}$ is the mean of the expectation distribution of the firms. The interpretation of $\frac{1}{\zeta}$ can be thought of the degree of uncertainty that firms have regarding exclusion decisions. With the additional assumption $\hat{\tau} = \bar{\tau}$ we have the distribution of expectations and firm choice and can obtain a solution for the firm legitimacy cutoff, where firms decide to file above and do not file below. Firms will decide to file an application with legitimacy l_i based on the probability their request has value greater than the cutoff plus cost.

$$
\begin{aligned}
l_i \geq F(\tau) + c &\implies l_i \geq \bar{\tau} + \varepsilon + c \\
&\implies \mathbb{E}(\varepsilon \leq l_i - \bar{\tau} - c) \\
&\implies [l_i - \bar{\tau} - c + \frac{1}{2\zeta}]\zeta \\
&\implies \frac{1}{2} + [l_i - \bar{\tau} - c]\zeta
\end{aligned} \tag{1}
$$

Setting the above expression to 0 and solve for l we get:

$$
\hat{l} = \bar{\tau} + c - \frac{1}{2\zeta} \tag{2}
$$

From this expression, we have the following comparative static results. As uncertainty increases, the legitimacy threshold falls. In particular, if we consider the two limit extremes:

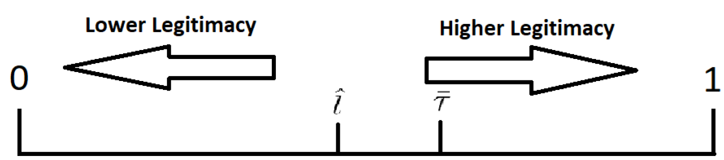
$$
\lim_{\frac{1}{\zeta} \to \infty} \hat{l} \to 0
$$

$$
\lim_{\frac{1}{\zeta} \to 0} \hat{l} \to \hat{\tau} + c
$$

As the process gets more uncertain, more applications are filed, and as uncertainty approaches infinity, applications with near no legitimacy are filed. This is mainly due to costs remaining fixed, hence firms will want to file requests as the exclusion can be profitable. As the process becomes clearer to firms, we approach the perfect information scenario in which firms will only file if their request legitimacy is greater than the $\hat{\tau} + c$.

As the cost of filing an application increases, the legitimacy threshold in which applications are filed increases. Let's assume we are in a world where $c < 1/2\zeta$, then we will have $\hat{l} < \bar{\tau}$. In terms of our model, this assumption is that the cost relative to uncertainty is sufficiently small so that the uncertainty leads to firms to file under the threshold $\bar{\tau}$, leading to some applications being denied. This does not seem to be a strong assumption as in the data nearly 90% of applications are denied.

Figure 3: Quality of Requests



From the Figure 3, it can be seen that we could calculate the approval rates by the proportion of approved exclusions over the proportion of requested exclusions as we have a uniform distribution.

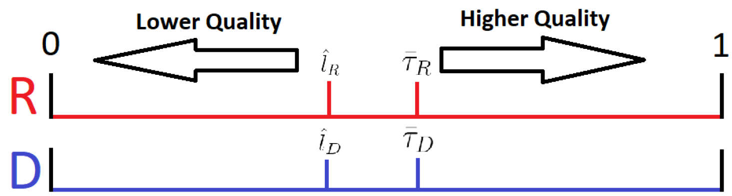
$$\text{Approval Rate} = r = \frac{1-\bar{\tau}}{1-\hat{l}} = \frac{1-\bar{\tau}}{1-\bar{\tau}-c+\frac{1}{2\zeta}} \tag{3}$$

We can then see that an increase in costs leads to a higher approval rate. An increase in uncertainty (decrease in ζ) leads to a decrease in approval rate. A increase of the quality threshold of the agency would increase the approval rates[9]

Going forward, to be able to compare results between two different groups, Republicans and Democrats in our case, we keep with our simplifying assumption of uniform distributions and further assume identical distributions for Republicans and Democrats.

[9]Note this is based on the assumption that the subsequent expectations of the firm also adjusts. If expectations of the firm did not adjust, $\hat{l}$ would not change and and increase in $\bar{\tau}$ would lead to a decrease in approval rates.

Figure 4: Quality of Requests - Republicans and Democrats



We will consider four main cases: two cases of rational expectations in Section 5.2 and two cases of nonrational expectations in Section 5.3.

5.2 Rational Expectations

For rational expectations, we need to consider two different scenarios. The first is the simplest case in the four considered, however, we include it for completeness. This is the case in which firms expect an unbiased process and the process is indeed completely unbiased. We can view this as solving the main model Republicans and Democrats separately. Since there is no bias, $\bar{\tau}_R = \bar{\tau}_D$. Firms will have the same information in this model, and as a result they will make the exact same choice $\hat{l}$. This would just be the case illustrated in Figure 4.

We now want to consider the other case of rational expectations, that there is bias in the process for exclusions and it is expected through the mean by firms. As it was known by firms that the process was being undertaken by the USTR, it may be the case in which the bias was expected. We can model this by returning to $\bar{\tau}$. We would interpret bias in the process as a difference in $\bar{\tau}$ for Republicans and Democrats. Hence ,there are differences in the expectations of $\bar{\tau}$. Following similar steps as above:

Democrats

$$\begin{aligned} F_D(\tau) &= \bar{\tau}_D + \varepsilon, \\ \text{where } \varepsilon &\sim \mathbb{U}[-\frac{1}{2\zeta}, \frac{1}{2\zeta}] \\ \hat{l}_D &= \bar{\tau}_D + c - \frac{1}{2\zeta} \\ r_D &= \frac{1 - \bar{\tau}_D}{1 - \bar{\tau}_D - c + \frac{1}{2\zeta}} \end{aligned}$$

Republicans

$$\begin{aligned} F_R(\tau) &= \bar{\tau}_R + \varepsilon, \\ \text{where } \varepsilon &\sim \mathbb{U}[-\frac{1}{2\zeta}, \frac{1}{2\zeta}] \\ \hat{l}_R &= \bar{\tau}_R + c - \frac{1}{2\zeta} \\ r_R &= \frac{1 - \bar{\tau}_R}{1 - \bar{\tau}_R - c + \frac{1}{2\zeta}} \end{aligned}$$

Theorem 5.1. *If we assume that there is a bias under rational expectations and the same amount of uncertainty about $\bar{\tau}_i$ for $i \in \{R, D\}$, then the model generates a decrease in legitimacy of applications filed and a higher approval rate for the party the bias favors.*

Proof. Without loss of generality assume $\bar{\tau}_R < \bar{\tau}_D$, then there exists some $b > 0$ such that $\bar{\tau}_R + b = \bar{\tau}_D$, then we can rewrite the above approval rates for Republicans as

$$r_R = \frac{1 - \bar{\tau}_D + b}{1 - \bar{\tau}_D + b - c + \frac{1}{2\zeta}}$$

We then want to know the slope of $r_R - r_D$ in b,

$$r_R - r_D = \frac{1 - \bar{\tau}_D + b}{1 - \bar{\tau}_D + b - c + \frac{1}{2\zeta}} - \frac{1 - \bar{\tau}_D}{1 - \bar{\tau}_D - c + \frac{1}{2\zeta}}$$

$$\frac{\partial(r_R - r_D)}{\partial b}$$

$$= \frac{1 - \bar{\tau}_D + b - c + \frac{1}{2\zeta} - [1 - \bar{\tau}_D + b]}{[1 - \bar{\tau}_D + b - c + \frac{1}{2\zeta]}^2}$$

$$= \frac{-c + \frac{1}{2}\zeta}{[1 - \bar{\tau}_D + b - c + \frac{1}{2\zeta}]^2}$$

$\frac{\partial(r_R - r_D)}{\partial b} > 0$ follows directly assumption that $c < \frac{1}{2\zeta}$. □

Note that the above is derived under the assumption that firms fully anticipate the bias through the mean of the expectation distribution. If we have a case where firms have an expectation of bias that is not equal to the actual bias, it will depend on the differences of the mean expectation versus the actual bias.

5.3 Nonrational Expectations

Now we consider the possibility that $\hat{\tau}$, the firm's expectation of τ, is not $\bar{\tau}$. This could arise from firms expecting a process to be biased and it is not, or in which the firms expect an unbiased process that is in fact biased. We can conceptually think about this by shifting of one of the values in Figure 4.

First, let us consider the case in which firms incorrectly assume that there is a bias when there is not. In this case, we will have a situation in which firms expecting the bias will file marginally worse applications, while the agency will remain at the unbiased point. Hence, this is a case in which the party expecting the bias will file more applications and have a lower approval rate relative to the rational case.

Next, we consider the case in which the process is biased but firms do not expect it to be. Relative to the rational case, the firms have the same legitimacy threshold. However, now there is one party that the process is biased towards. This party will then have higher approval rates, since the party's legitimacy threshold for exclusion approval is lower.

5.4 Discussion on Model Findings

The following table summarizes the main findings of the model including all four combinations of expected bias or not and actual bias or not. As the problem would be symmetrical for a Democratic bias, we can just consider the other cases as the flipping of the subscripts.

Table 2: Basic Model Results

		Expectations of Republican Bias	
		Yes	No
Actual Republican Bias	Yes	$\hat{l}_R < \hat{l}_D$ $r_R > r_D$	$\hat{l}_R = \hat{l}_D$ $r_R > r_D$
	No	$\hat{l}_R < \hat{l}_D$ $r_R < r_D$	$\hat{l}_R = \hat{l}_D$ $r_R = r_D$

Are firms in Democratic or Republican regions more likely to be harmed by the Section 301 tariffs, therefore having a stronger case for exclusions? Our model assumes the same distribution of legitimacy of requests. Without differences in legitimacy distributions, we could simply look at approval rates, however, we view identical distributions of potential requests for Democrat and Republicans as a much too strong restriction in reality.

Autor et al. (2013) find that it is regions that strongly correlate with the Republican vote share that are most impacted by trade with China. Dorn et al. (2020) have shown that areas more exposed to trade have increased levels of polarization. They also show that the trade exposure caused non-negligible gains for Republican areas in the 2016 election. Meanwhile Fajgelbaum et al. (2020) assesses the impact of U.S. trade war with all countries and finds that it is swing counties that receive the most protection from import tariffs. In our case we are considering cases where firms are importers (otherwise it would not make sense for them to be filing for a request), while Fajgelbaum et al. (2020) is assessing the protection received by domestic producers [10].

We believe that our empirical story is most likely to fit the case of the top left of our table in which there was some expectations of bias and actual bias in the process. Based on this conclusion, we take special care in our identification to control for differences in the distributions. Our interpretation of our results is a measure of differences in $\bar{\tau}$ for Republicans and Democrats.

6 Empirical Methodology

We estimate probability models to investigate the effect of the Republican vote share on the probability that a firm from that county received an exclusion approval. In particular we are

[10] Another key difference between thinking about our study and Fajgelbaum et al. (2020) is that they look at import tariffs from all countries, while the exclusion requests were for tariffs on Chinese imports.

interested in controlling for potential differences in request distributions, leaving us with a measure for $\bar{\tau}_R - \bar{\tau}_D$.

The base of our specification is:

$$\begin{aligned} 1\{Approval_{ifpc}\} = &\beta_0 + \beta_1 \text{Republican share}_c + \beta_2 \text{China Import Share}_p + \\ &\beta_3 log(\text{Value of Imports})_p + \Omega P_p + \Gamma F_f + \Phi C_c + \epsilon_{ifpc} \end{aligned} \tag{4}$$

where the dependent variable is a binary indicator whether a petition i is approved by a firm f based in the county c for a product p. We control for various product level (P), firm level (F), and county level labor market characteristics (C), such as the number of petitions, number of firms, dependence on Chinese imports, firm size, and county-level unemployment rate.

We estimate β_1, the relationship between the Republican vote share and approval rates in three different ways.

Our first way is to fit a cubic function in the Republican vote share in the above Equation 4. Motivated by Lindbeck and Weibull (1987, 1993) to our case, if a bias is present, we expect it to appear as an inverted u-shape relationship where the mixed counties receive the highest approval rates.

We then allow the Republican vote share in the Equation 4 to vary nonlinearly and discontinuously by classifying the Republican vote share into different bins. This approach is motivated both by testing for the inverted u-relationship as in the theory of Lindbeck and Weibull (1987, 1993), but also Cox and McCubbins (1986) where we would expect to see the Republican vote share to be positively related to approval rates. In particular if the inverted u-shape held, our bin classification around the mixed counties should pick up the highest probability of approval. If the other theory held, we would expect the bin with the largest Republican vote share to have the highest probability of approval.

Lastly, we allow for a linear relationship in the Republican vote share. While this regression is not very informative about the nonlinear relationship. It is informative for Cox and McCubbins (1986) where we would expect to see a positive coefficient.

Outside of concerns about the selection effect brought forth in Section 5, we are not concerned about endogeneity of the Republican vote share conditional on our controls, that is we believe we have controlled for differences in potential request distributions through our product and firm controls. One common concern in non-experimental designs is simultaneity. As the Section 301 tariffs were not imposed until the Trump Administration was in office and the process for Section 301 tariff exclusions was not even in talk prior to the imposition of the tariffs, we are not concerned about the potential for simultaneity.

Although, conditional on all of our controls we are not worried about endogeneity concerns, we admit some may not be convinced. For example, while the process was not introduced until after the election, it could be the case that voters in Republican areas did not expect in particular a tariff exclusion, they may have expected favors in general. It just so happens that in our case it is tariff exclusions.

To further address these potential endogeneity concerns we additionally estimate our regression by instrumenting the Republican vote share with two different potential instruments. The ideal instrument in our case would be a variable that is correlated with our endogenous variable of interest, the 2016 Republican vote share, and uncorrelated with our error term after including our control variables. There has been an extensive surveys on analyzing demographic groups, their political leanings, and voting trends. One of these groups that surveys voters is the Pew Research Center. In the exit poll of their 2016 election, they found that 91% of African American voters voted for the Democratic candidate for President while only 6% voted for the Republican candidate. They also found that election results spread along very deep ideological lines. The share of ideologically Democrats who voted Democrat for the President were 94%, while for Republican's were 92%. For voters with ideologies leaning Democrat or Republican, they both voted 89% for the party they leaned towards ideologically.

The two different instruments we employ are: the share of African Americans in each county and the 2012 Republican vote share. We argue that these instruments are not correlated with the error term but with our variable of interest.

The share of African Americans in each county is a good instrument because it is inversely related to the 2016 Republican vote share. Research has shown that, historically, African Americans tend to vote for the Democrat party. We argue that this instrument is unrelated to the error term since the share of African Americans in a county should not influence the approval of tariff exclusions, except through our variable of interest, the share of Republican voters.

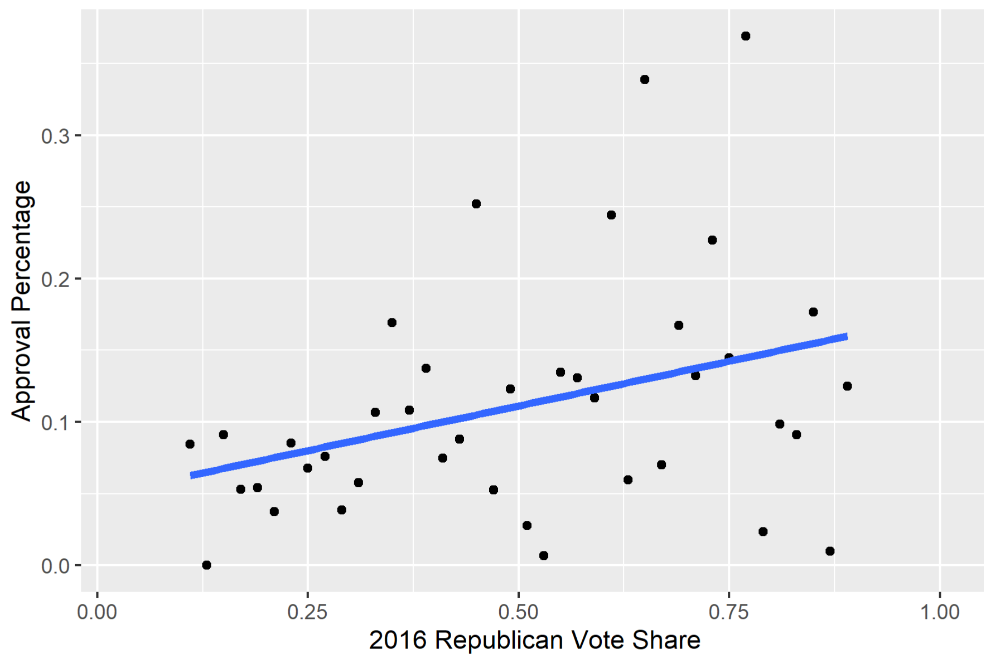
The 2012 Republican vote share could also be considered an instrument to our variable of interest because voting patterns tend to persist through time. Figure 11 shows the difference between the Republican vote shares in 2016 and 2012, and we observe that there was minimal change in voting patterns. We also argue that this instrument is unlikely to be correlated with the error term because trade policy was a main voting concern only in 2016, not in 2012 according to the Pew Research Center. While, this meets our conditions for instrument validity, it could still pose issues with controlling for omitted variables. That is, the omitted variable bias could stem from other variables unrelated to the 2016 voting behavior. Therefore, the better instruments for our empirical analysis would be the vote share of African Americans in each county.

7 Results

We first investigate the relationship between the Republican vote share and approval rates. We do this by first classifying exclusion requests into bins based on the Republican vote share for the county of the requesting firm. For each bin of width 2% of the Republican vote share, we calculate the ratio of exclusion requests approved to total requests made. For example if we have 400 requests coming from firms in counties with between 46% and 48% Republican vote share and 100 of these were approved, then this bin would have an approval rate of 25%.

In Figure 5 we plot this at the midpoint of the Republican vote share, 47% in our example above.

Figure 5: Percentage of Exclusions Approved by Republican Share Group

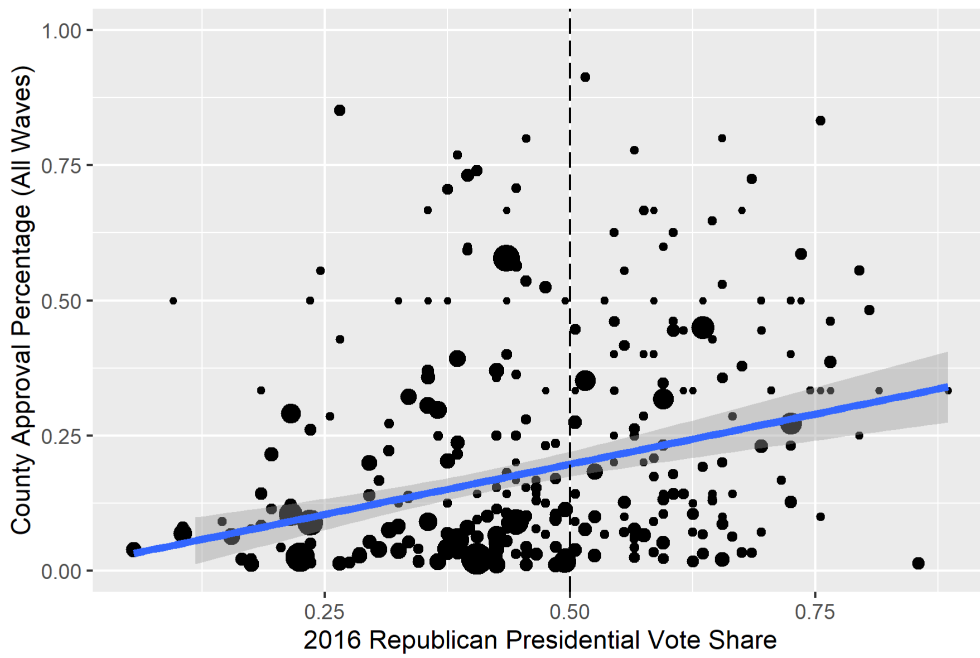


We show the positive relationship in Figure 5 with our classification of bins of width of 2%. While this trend is informative, the bin size is quite arbitrary, we further investigate by classifying approval rates by county.

Rates are calculated by taking the proportion of products that were approved from all the exclusion requests made for exclusions for each county. In Figure 6 we graph the calculated approval rates against the Republican vote share, and we find that there is a positive relationship between the two variables.[11]

[11]Figure 14 in the appendix illustrates the relationship between the approval rates and the Republican vote share across all waves of tariff exclusions. In this figure, each point represents a unique county, and the point size proportional to the number of requests from that county. We also extend this investigation by accounting for the set of tariffs in each wave (as seen in Figure 14, and we still observe the positive relationship.

Figure 6: Approval Rates by County



7.1 Ordinary Least Squares

To quantify the effect of the Republican vote share on the approval rates, we estimate our empirical model which is equation 4. Our primary variable of interest in each model is the share of voters in the county where firm f is located who voted Republican in the 2016 Presidential election. In controlling for product heterogeneity, we follow U.S. Government Accountability Office (2021). The estimation controls for the primary end use of a product and the product being high tech or important to public health. We also control for firm size, the number of requests made by a firm, and unemployment rates in each county.

We begin by reporting our main result in which Republican Share is a predefined as a linear relationship with exclusion approval after accounting for all of our controls. In estimating this relationship, we first employ a simple linear probability model. Column (1) in Table 3 reports the result of using the product controls from U.S. Government Accountability Office (2021) and adding in the 2016 Republican vote share. Column (2) in Table 3 reports the result of adding in controls for the size of the firm and county level unemployment data. Column (3) in Table 3 reports the results of removing the product controls in U.S. Government Accountability Office (2021) and instead using HS 6 fixed effects.

Table 3: OLS Regressions

Dependent Variable: Exclusion Approved			
	(1)	(2)	(3)
2016 Republican Vote Share	0.112^{***}	0.090^{**}	0.052^{***}
(County)	(0.013)	(0.013)	(0.016)
China's Share of Imports	0.118^{***}	0.116^{***}	
(HTSUS 10)	(0.008)	(0.008)	
Log of Value Imports	-0.009^{***}	-0.009^{***}	
(HTSUS 10)	(0.001)	(0.001)	
Product Characteristics	Yes	Yes	No
Firm Size Controls	No	Yes	Yes
County Unemployment	No	Yes	Yes
HS 6 Fixed Effects	No	No	Yes
Observations	34,552	34,552	34,552
R^2	0.217	0.219	0.495
Adjusted R^2	0.216	0.219	0.471

*p<0.1; **p<0.05; ***p<0.01

Notes: Robust standard errors in parentheses. Full regression results can be found in Table 8 in the Appendix.

The results indicate that the 2016 Republican vote share has a positive influence on the probability of getting an approved tariff exclusion. That is, firms from counties that voted more heavily Republican, in the 2016 Presidential election, received higher rates of exclusions from the USTR. Interpreting the results, a 10% increase in the Republican vote share leads to an approximate increase of 1% in the probability of approval. Relative to the mean, this is about a 10% increase in approval rate. However as discussed this could support either theories as we may be forcing a linear specification to a non-linear relationship.

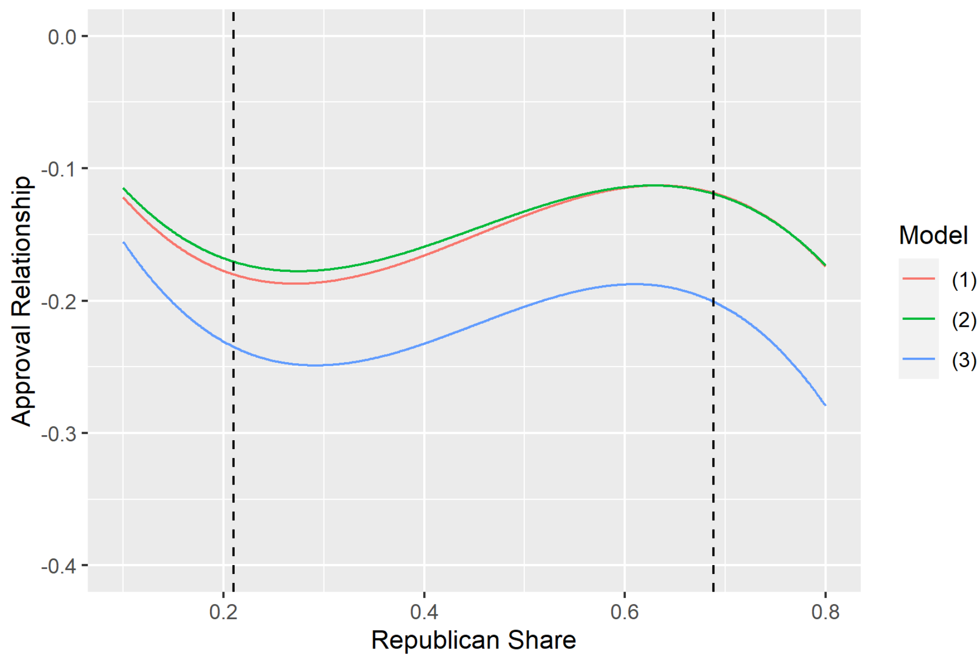
7.2 Nonlinearity

We proceed by fitting the 2016 Republican vote share to a cubic function, conditional on all other controls. The full regression results can be found in the appendix, as it's more difficult to interpret coefficients of the cubic relationship without plotting, we graph the relationship below. For example, the specification in Table 10 Column (1) we plot the function

$$y = -1.609 \cdot x + 4.233 \cdot x^2 - 3.117 \cdot x^3$$

where x is the 2016 Republican vote share and y is it's relationship with exclusion approval. We plot this and the other two columns from Table 10 in Figure 7. As this relationship only makes sense for a specific domain of values in which we are observing the 2016 Republican vote share, we additionally plot vertical dotted lines to denote the 5^{th} and 95^{th} percentiles of the Republican vote share distribution in our data set. Our two main takeaways are that we can see that in each case a linear approximation seems to capture the relationship quite well and that we do not see any evidence for the hypothesis of the mixed counties receiving the highest rate of approvals. It is still the predominantly Republican areas receiving the largest approval rates.

Figure 7: Cubic Relationship: Republican Vote Share and Exclusion Approval



7.3 Nonlinearities and Discontinuities

While the cubic function allows for nonlinearity it does not allow for discontinuities. To investigate this possibility we define dummy variables for various different sized bins. In particular we investigate a differential effect about areas that are close to 50% Republican vote share (swing areas). Allowing a different level of effect for the Republican vote share between 48% and 52%.

In addition to this more local definition of swing county we took, we also take the definition of mixed county that Fajgelbaum et al. (2020) uses in their analyses. That is we define a bin to be between 40% and 60% Republican vote share, their definition of mixed county.

We report results from the two different bin ranges in Table 4. The full regressions can be found in the appendix in Table 11 and Table 12. However in each case the reference group is the group of that has the least Republican vote share. In the first two rows of results it would be relative to the group with Republican vote share less than 48%. In the second group it would be relative to less than 40%. We find that in our more local definition of the competitive range, between 48% and 52% vote share has the lowest approval rate relative to the less Republican range, however this relationship is not robust to all of our specifications. For following Fajgelbaum et al. (2020) we find for two of our three specifications that the mixed counties receive higher exclusion approval relative to the less than 40% Republican vote share group. However in both these cases, the greater than 60% vote share is even larger.

Table 4: Republican vote share in bins - OLS

Dependent Variable: Exclusion Approved			
	(1)	(2)	(3)
$48\% \leq$ Rep Share $\leq 52\%$	-0.014^{***}	-0.016^{***}	0.002
(Binary)	(0.005)	(0.005)	(0.007)
Rep Share $> 52\%$	0.046^{***}	0.039^{***}	0.027^{***}
(Binary)	(0.005)	(0.005)	(0.006)
$40\% \leq$ Rep Share $\leq 60\%$	0.023^{***}	0.019^{***}	0.002
(Binary)	(0.004)	(0.004)	(0.005)
Rep Share $> 60\%$	0.058^{***}	0.050^{***}	0.032^{***}
(Binary)	(0.007)	(0.007)	(0.008)
Product Characteristics	Yes	Yes	No
Firm Size Controls	No	Yes	Yes
County Unemployment	No	Yes	Yes
HS 6 Fixed Effects	No	No	Yes
Observations	34,552	34,552	34,552

*p<0.1; **p<0.05; ***p<0.01

Notes: Robust standard errors in parentheses. Main variable of interest from two different regressions reported: Table 11 and Table 12 report full results.

Across both specifications the highest Republican vote share bin holds the largest effect on Approval Rates. We view this as further support for the theory of rewarding one's core base, while not finding evidence for the mixed vote share theory.

7.4 Instrumental Variable Approach

While the exclusion process was not introduced until after the election, it could be the case that voters in Republican areas did not expect in particular a tariff exclusion, they may have expected favors in general. To account for this potential issue of endogeneity conditional on our controls, we estimate our model, instrumenting the 2016 Republican vote share. In testing for the validity of our instruments, we conduct a heteroskedastic robust F-stastic on the first stage regression and report results in Table 5. We find that, for both instruments, we have enough evidence to reject the null hypothesis. That is, we find that both instruments are correlated with our variable of interest.

Table 5: Heteroskedastic Robust F-statistic

	IV: Af Am Share	IV: Rep 2012	IV: Both
	(1)	(2)	(3)
F	1706.4	56080	31066
Pr(>F)	<2.2e-16	<2.2e-16	<2.2e-16

Notes: Degrees of freedom of 1, 1, and 2 respectively.

In Table 6 Column (1) reports the results of our original OLS regression, Columns (2) and (3) shows our estimation using instruments: share of population that is African-American in a county and 2012 county Republican vote share, respectively. Quantitatively, there are only small changes across specifications. Across both the ordinary least squares and IV estimates our point estimates range from 0.09 to 0.12.

Table 6: Instrumental Variables Results

	Dependent Variable: Exclusion Approved		
	IV: Af Am Share	IV: Rep 2012	IV: Both
	(1)	(2)	(3)
2016 Republican Vote Share	0.117***	0.095**	0.095***
(County)	(0.048)	(0.014)	(0.014)
China's Share of Imports	0.115***	0.115***	0.115***
(HTSUS 10)	(0.008)	(0.008)	(0.008)
Log of Value Imports	-0.009***	-0.009***	-0.009***
(HTSUS 10)	(0.001)	(0.001)	(0.001)
Product Characteristics	Yes	Yes	Yes
Firm Size Controls	Yes	Yes	Yes
County Unemployment	Yes	Yes	Yes
Observations	34,552	34,552	34,552
R^2	0.219	0.219	0.219
Adjusted R^2	0.219	0.218	0.219

*p<0.1; **p<0.05; ***p<0.01

Notes: Robust standard errors in parentheses. Full regression results can be found in Table 9 in the Appendix.

Column (3) in Table 6 we instrument one variable with two instruments. For this specification we run the overidentification test (J-test) and obtain a p-value of 0.223. We hence fail to reject the null hypothesis that all instruments are exogenous. While this test does not show that are instruments are valid, it is another piece of evidence to support our argument for these instruments.

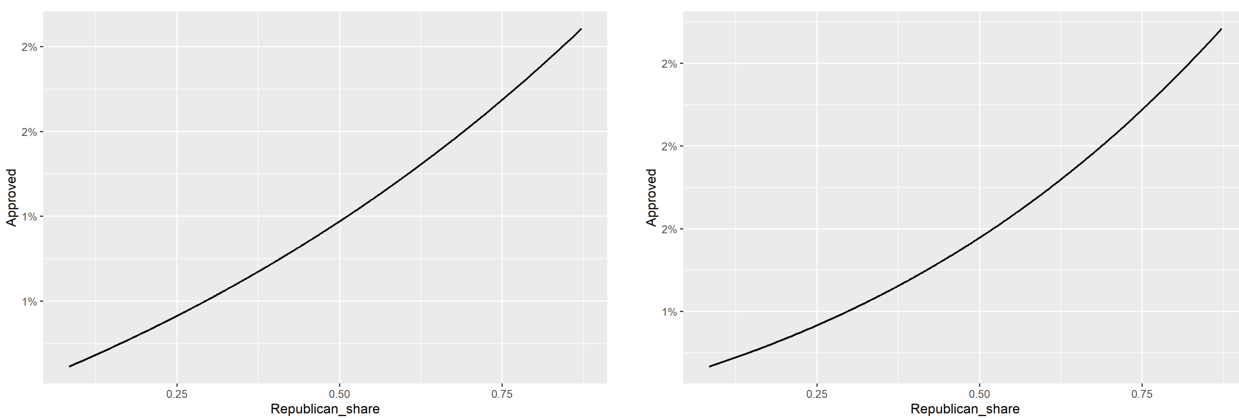
7.5 Logit and Probit

With a dichotomous dependent variable, we are concerned about nonlinear relationships. We run Logit and Probit models with all of the controls we included in Equation 4 to check for this. We report the marginal effects of the average application for Republican vote share below in Table 7 and the table of marginal effects for all regressors in Table 13 in the appendix. Additionally to visually check for the case in which the marginal effect was stronger for some regions of the distribution than the other, we plot the predicted probabilities over the range of the Republican vote share values in Figure 8. We can see that the relationship is approximately linear, thus marginal effect is roughly constant.

Table 7: Logit and Probit Marginal Effects

Dependent Variable: Exclusion Approved		
	Probit	Logistic
2016 Republican Vote Share	0.072***	0.059***
Observations	34,552	34,552

Figure 8: Predicted Probabilities of Approval in Logistic and Probit Model



Notes: Marginal effects from logistic model on left panel, probit model to the right.

8 Conclusion

The Trump administration has imposed Section 301 tariffs against Chinese imports, which harmed American firms. To alleviate the tariff burden on the affected firms, the Trump administration has allowed the firms to file an appeal for a tariff exclusion through the USTR. However, the USTR president is appointed by the US President, which can result in favorable outcomes in areas supportive of the US President.

Using data on tariff exclusion requests and approvals web-scraped from USTR portal and from QuantGov, cross-referencing Orbis firm data, and product characteristics we are able to show through a linear probability model that a 10 percentage point increase in the Republican vote share in a county increases approval probability by approximately 10%. We account for the possibility of omitted variables through our IV approach and the potential nonlinearities and discontinuities through both classifying the Republican vote share into bins and estimating a cubic function in the Republican vote share. In each of these cases the pattern of higher approvals for heavy Republican vote share counties holds.

Fajgelbaum et al. (2020) found that it was politically mixed counties that received the most protection from the import tariffs imposed on other countries. . They also found that impacts of retaliation seemed to be an increasing function of the Republican vote share. Fetzer and Schwarz (2021) extends their analysis to China specific retaliation and show further evidence for political targeting. We add another layer to this story by evaluating exclusion requests for import tariffs from China and find the probability of approval is related to the political makeup of the county of the applying firm.

It seems within this story there is a mixture of two theories within the political science and political economy literature. The initial tariffs appear to be consistent with the story of influencing swing areas, while both the retaliation and exclusion process seem to be more consistent with a story of rewarding ones loyal base. We do not know of a theory which can parsimoniously explain or attempts to explain all of these motives within one framework. We view this as a very interesting line of future research.

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Appendix A Data Summary and Plots

Figure 9: 2016 Republican Vote Share

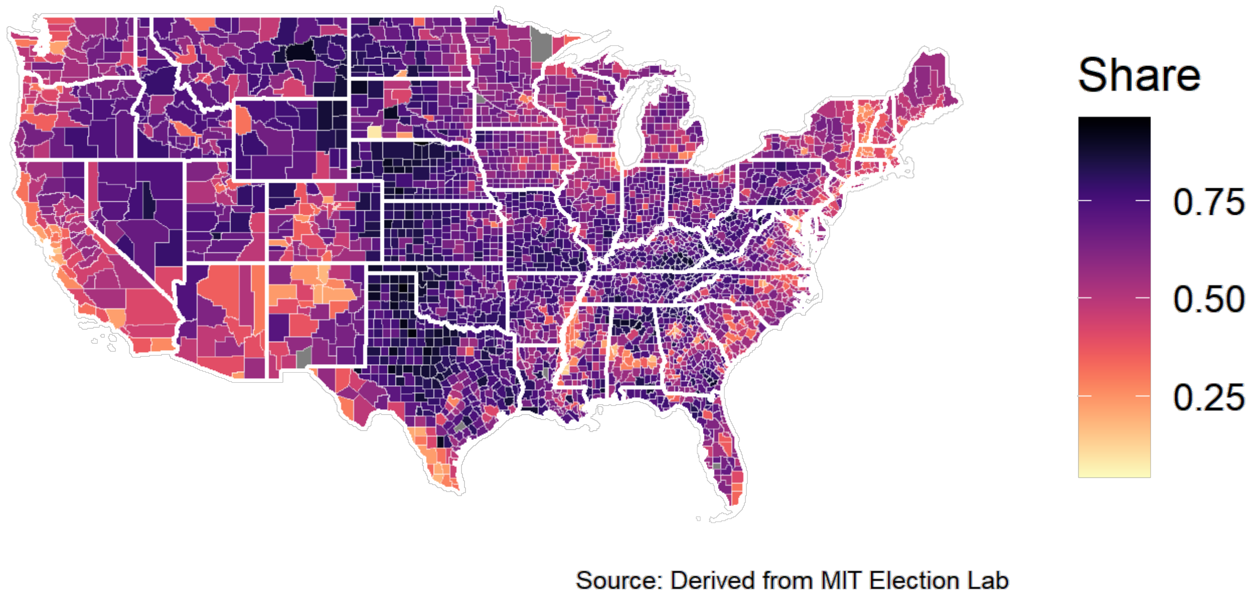


Figure 10: 2012 Republican Vote Share

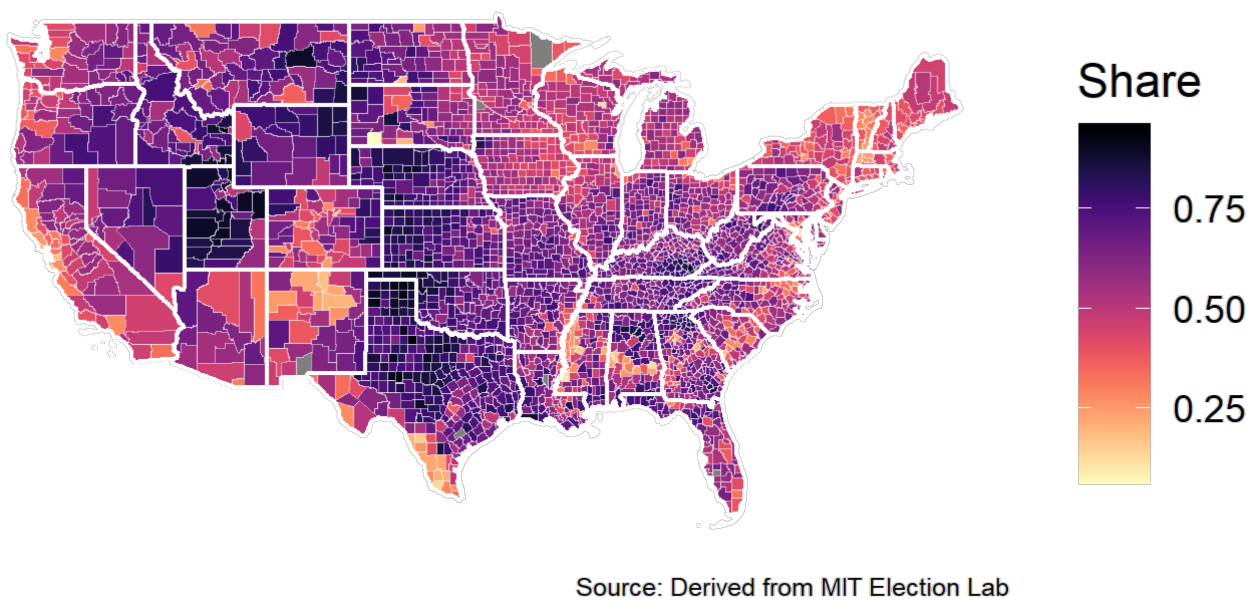


Figure 11: Difference between 2012 and 2016 Republican Vote Share

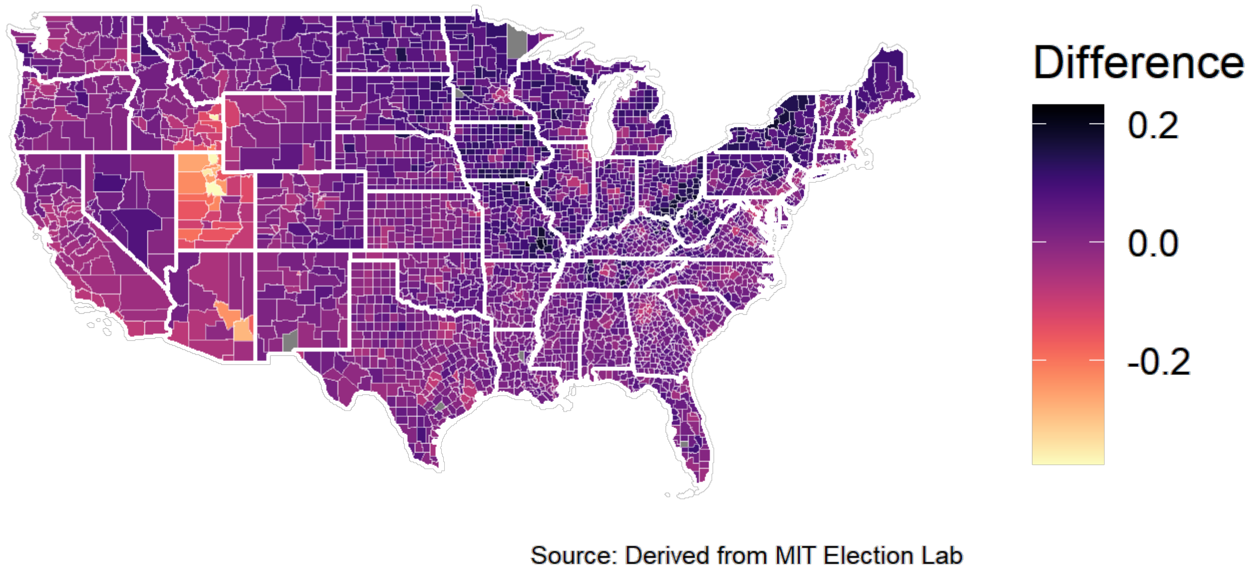


Figure 12: 2017 Unemployment Rate

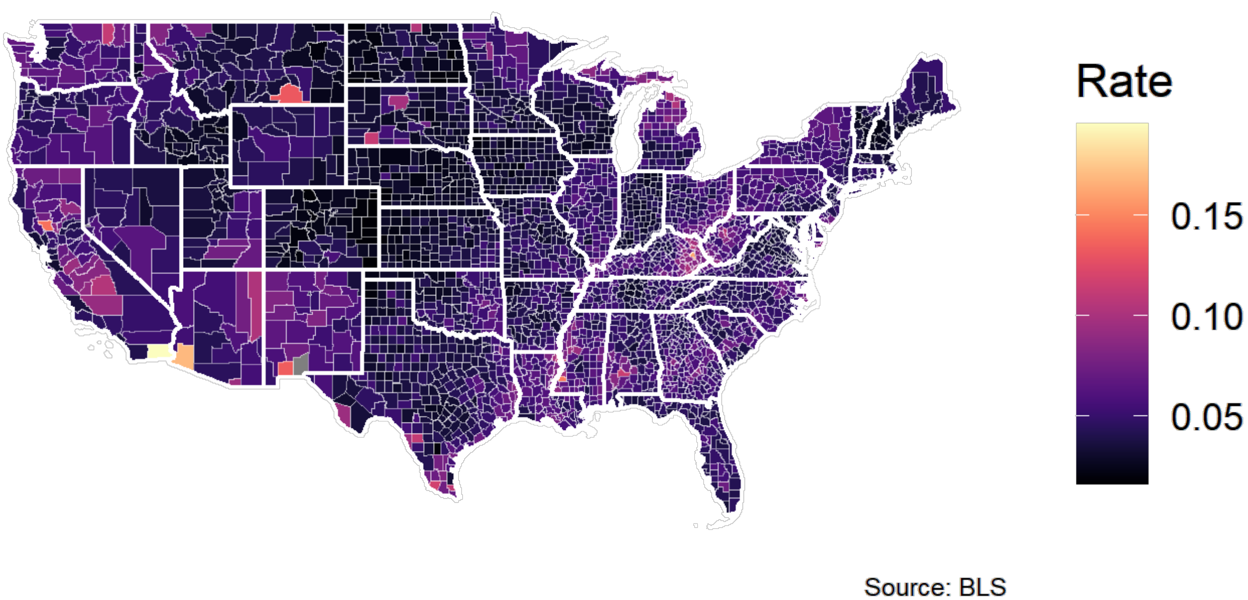
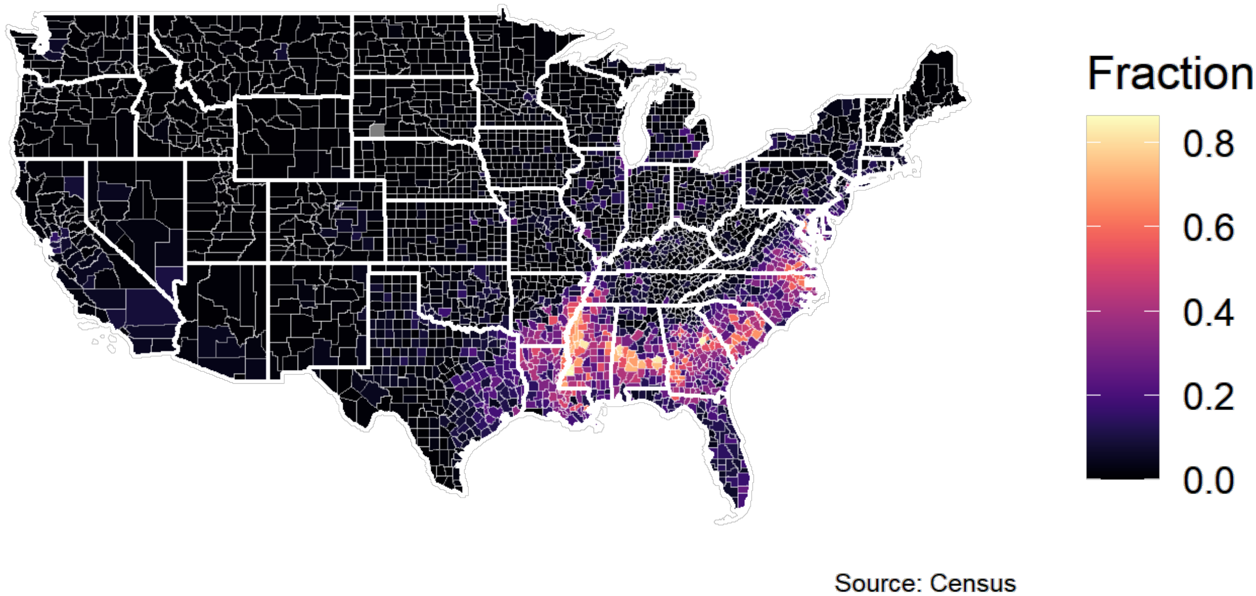


Figure 13: African American's Share of 2010 Population



Appendix B Results

Figure 14: Approval Rate within County by Wave

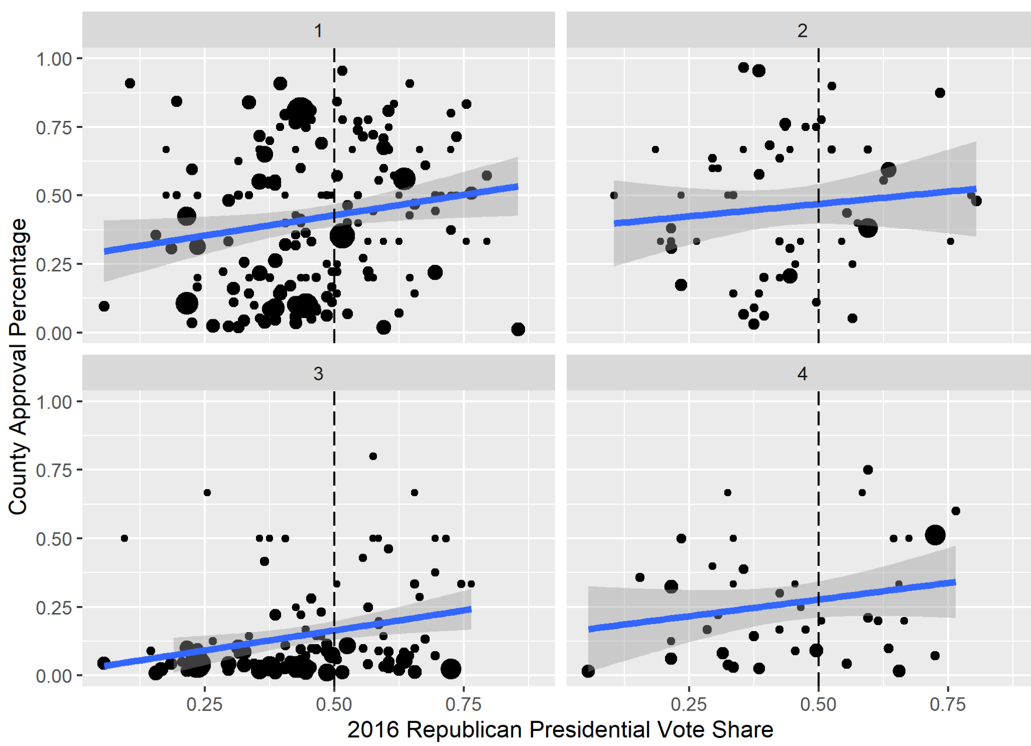


Table 8: Basic Linear Probability Models

	Dependent Variable: Exclusion Approved			
	(1)	(2)	(3)	(4)
2016 Republican Share		0.112^{***}	0.090^{***}	0.052^{***}
(County)		(0.013)	(0.013)	(0.016)
Wave 3 or 4a	-0.280^{***}	-0.276^{***}	-0.283^{***}	-0.079^{***}
(Binary)	(0.006)	(0.006)	(0.006)	(0.022)
Capital End-Use	0.065^{***}	0.062^{***}	0.060^{***}	
(Binary)	(0.004)	(0.004)	(0.004)	
Industrial End-Use	0.019^{***}	0.013^{***}	0.014^{***}	
(Binary)	(0.004)	(0.004)	(0.004)	
Automotive End-Use	0.024^{***}	0.029^{***}	0.028^{***}	
(Binary)	(0.005)	(0.005)	(0.005)	
Other End-Use	0.076^{***}	0.080^{***}	0.082^{***}	
(Binary)	(0.019)	(0.019)	(0.019)	
Public Health Good	0.163^{***}	0.169^{***}	0.168^{***}	
(Binary)	(0.023)	(0.023)	(0.023)	
Advanced Technology	0.017	0.022^{*}	0.017	
(Binary)	(0.012)	(0.012)	(0.013)	
Log of World Imports	-0.008^{***}	-0.009^{***}	-0.009^{***}	
(HTSUS 10)	(0.001)	(0.001)	(0.001)	
China's Share of Imports	0.123^{***}	0.118^{***}	0.116^{***}	
(HTSUS 10)	(0.008)	(0.008)	(0.008)	
Log of Industry Employ	0.010^{***}	0.009^{***}	0.009^{***}	
(NAICS)	(0.002)	(0.002)	(0.002)	
Log of Exclusion Requests	0.0004	-0.0002	-0.001	0.005^{***}
(Firm)	(0.001)	(0.001)	(0.001)	(0.001)
Maximum Requesting Firm	0.007	-0.004	-0.011^{**}	-0.033^{***}
(Binary)	(0.005)	(0.005)	(0.005)	(0.007)
Log of Num Employees			0.002	0.013^{***}
(Firm)			(0.002)	(0.003)
Log Operating Revenue Turnover			-0.003	-0.011^{***}
(Firm)			(0.002)	(0.003)
2017 Unemployment Rate			-0.0002^{***}	-0.0002^{***}
(County)			(0.00002)	(0.00002)
HS 6 Fixed Effects:	No	No	No	Yes
Observations	34,552	34,552	34,552	34,552
R^2	0.214	0.217	0.219	0.495
Adjusted R^2	0.214	0.216	0.219	0.471

Note: *p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses

Table 9: Instrumenting the 2016 Republican Vote Share

	Dependent Variable: Exclusion Approved		
	IV: Af Am Share	IV: Rep 2012	IV: Both
	(1)	(2)	(3)
2016 Republican Share	0.117**	0.095***	0.095***
(County)	(0.048)	(0.014)	(0.014)
Wave 3 or 4a	−0.282***	−0.283***	−0.283***
(Binary)	(0.007)	(0.006)	(0.006)
Capital End-Use	0.060***	0.060***	0.060***
(Binary)	(0.004)	(0.004)	(0.004)
Industrial End-Use	0.013***	0.014***	0.014***
(Binary)	(0.005)	(0.004)	(0.004)
Automotive End-Use	0.029***	0.028***	0.028***
(Binary)	(0.005)	(0.005)	(0.005)
Other End-Use	0.083***	0.082***	0.082***
(Binary)	(0.020)	(0.019)	(0.019)
Public Health Good	0.169***	0.168***	0.168***
(Binary)	(0.023)	(0.023)	(0.023)
Advanced Technology	0.018	0.017	0.017
(Binary)	(0.013)	(0.013)	(0.013)
Log of World Imports	−0.009***	−0.009***	−0.009***
(HTSUS 10)	(0.001)	(0.001)	(0.001)
China's Share of Imports	0.115***	0.115***	0.115***
(HTSUS 10)	(0.008)	(0.008)	(0.008)
Log of Industry Employ	0.009***	0.009***	0.009***
(NAICS)	(0.002)	(0.002)	(0.002)
Log of Exclusion Requests	−0.001	−0.001	−0.001
(Firm)	(0.001)	(0.001)	(0.001)
Maximum Requesting Firm	−0.013**	−0.011**	−0.011**
(Binary)	(0.007)	(0.005)	(0.005)
Log of Num Employees	0.002	0.002	0.002
(Firm)	(0.003)	(0.002)	(0.002)
Log Operating Revenue Turnover	−0.002	−0.002	−0.002
(Firm)	(0.002)	(0.002)	(0.002)
2017 Unemployment Rate	−0.0002***	−0.0002***	−0.0002***
(County)	(0.00003)	(0.00002)	(0.00002)
Observations	34,552	34,552	34,552
R^2	0.219	0.219	0.219
Adjusted R^2	0.218	0.219	0.219

Note: *p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses

Table 10: Cubic Function in Republican Share

	Dependent Variable: Exemption Approved		
	(1)	(2)	(3)
2016 Republican Share	-1.609^{***}	-1.514^{***}	-2.031^{***}
(County)	(0.182)	(0.182)	(0.240)
2016 Republican Share^2	4.233^{***}	3.958^{***}	5.147^{***}
(County)	(0.449)	(0.449)	(0.609)
2016 Republican Share^3	-3.117^{***}	-2.920^{***}	-3.806^{***}
(County)	(0.337)	(0.336)	(0.469)
Wave 3 or 4a	-0.277^{***}	-0.283^{***}	-0.080^{***}
(Binary)	(0.006)	(0.006)	(0.021)
Capital End-Use	0.067^{***}	0.064^{***}	
(Binary)	(0.004)	(0.004)	
Industrial End-Use	0.014^{***}	0.014^{***}	
(Binary)	(0.004)	(0.004)	
Automotive End-Use	0.033^{***}	0.032^{***}	
(Binary)	(0.005)	(0.005)	
Other End-Use	0.083^{***}	0.083^{***}	
(Binary)	(0.019)	(0.020)	
Public Health Good	0.169^{***}	0.169^{***}	
(Binary)	(0.023)	(0.023)	
Advanced Technology	0.015	0.011	
(Binary)	(0.012)	(0.013)	
Log of World Import Value	-0.009^{***}	-0.009^{***}	
(HTSUS 10)	(0.001)	(0.001)	
China's Share of Imports	0.118^{***}	0.115^{***}	
(HTSUS 10)	(0.008)	(0.008)	
Log of Industry Employ	0.009^{***}	0.010^{***}	
(NAICS)	(0.002)	(0.002)	
Log of Exclusion Requests	-0.0004	-0.001	0.004^{***}
(Firm)	(0.001)	(0.001)	(0.001)
Maximum Requesting Firm	-0.016^{***}	-0.023^{***}	-0.048^{***}
(Binary)	(0.005)	(0.005)	(0.008)
Log of Number Employees		0.002	0.014^{***}
(Firm)		(0.002)	(0.003)
Log Operating Revenue Turnover		-0.003	-0.011^{***}
(Firm)		(0.002)	(0.003)
2017 Unemployment Rate		-0.0002^{***}	-0.0002^{***}
(County)		(0.00002)	(0.00002)
HS 6 Fixed Effects	No	No	Yes
Observations	34,552	34,552	34,552
R^2	0.219	0.221	0.498
Adjusted R^2	0.219	0.221	0.474

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Robust standard errors in parentheses

Table 11: Republican Share Bins - Swing County

	Dependent Variable: Exemption Approved		
	(1)	(2)	(3)
$48\% \leq$ Rep Share $\leq 52\%$	-0.014^{***}	-0.016^{***}	0.002
(Binary)	(0.005)	(0.005)	(0.007)
Rep Share $> 52\%$	0.046^{***}	0.039^{***}	0.027^{***}
(Binary)	(0.005)	(0.005)	(0.006)
Wave 3 or 4a	-0.277^{***}	-0.283^{***}	-0.080^{***}
(Binary)	(0.006)	(0.006)	(0.022)
Capital End-Use	0.063^{***}	0.061^{***}	
(Binary)	(0.004)	(0.004)	
Industrial End-Use	0.024^{***}	0.024^{***}	
(Binary)	(0.004)	(0.004)	
Automotive End-Use	0.028^{***}	0.028^{***}	
(Binary)	(0.005)	(0.005)	
Other End-Use	0.077^{***}	0.078^{***}	
(Binary)	(0.019)	(0.019)	
Public Health Good	0.168^{***}	0.168^{***}	
(Binary)	(0.023)	(0.023)	
Advanced Technology	0.020	0.015	
(Binary)	(0.012)	(0.013)	
Log of World Import Value	-0.009^{***}	-0.009^{***}	
(HTSUS 10)	(0.001)	(0.001)	
China's Share of Imports	0.126^{***}	0.122^{***}	
(HTSUS 10)	(0.008)	(0.008)	
Log of Industry Employment	0.009^{***}	0.009^{***}	
(NAICS)	(0.002)	(0.002)	
Log of Exclusion Requests	0.001	0.00002	0.004^{***}
(Firm)	(0.001)	(0.001)	(0.001)
Maximum Requesting Firm	0.025^{***}	0.015^{***}	-0.023^{***}
(Binary)	(0.005)	(0.006)	(0.008)
Log of Number Employees		0.001	0.013^{***}
(Firm)		(0.002)	(0.003)
Log Operating Revenue Turnover		-0.002	-0.011^{***}
(Firm)		(0.002)	(0.003)
2017 Unemployment Rate		-0.017^{***}	-0.018^{***}
(County)		(0.002)	(0.002)
HS 6 Fixed Effects	No	No	Yes
Observations	34,552	34,552	34,552
R^2	0.218	0.220	0.496
Adjusted R^2	0.217	0.220	0.471

Note: *p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses

Table 12: Republican Vote Share Bins - Mixed County

	Dependent Variable: Exemption Approved		
	(1)	(2)	(3)
$40\% \leq$ Rep Share $\leq 60\%$	0.023^{***}	0.019^{***}	0.002
(Binary)	(0.004)	(0.004)	(0.005)
Rep Share $> 60\%$	0.058^{***}	0.050^{***}	0.032^{***}
(Binary)	(0.007)	(0.007)	(0.008)
Wave 3 or 4a	-0.275^{***}	-0.282^{***}	-0.082^{***}
(Binary)	(0.006)	(0.006)	(0.022)
Capital End-Use	0.065^{***}	0.062^{***}	
(Binary)	(0.004)	(0.004)	
Industrial End-Use	0.015^{***}	0.016^{***}	
(Binary)	(0.004)	(0.004)	
Automotive End-Use	0.030^{***}	0.029^{***}	
(Binary)	(0.005)	(0.005)	
Other End-Use	0.078^{***}	0.081^{***}	
(Binary)	(0.019)	(0.019)	
Public Health Good	0.170^{***}	0.169^{***}	
(Binary)	(0.023)	(0.023)	
Advanced Technology	0.018	0.014	
(Binary)	(0.012)	(0.013)	
Log of World Imports	-0.009^{***}	-0.009^{***}	
(HTSUS 10)	(0.001)	(0.001)	
China's Share of Imports	0.120^{***}	0.117^{***}	
(HTSUS 10)	(0.008)	(0.008)	
Log of Industry Employ	0.008^{***}	0.009^{***}	
(NAICS)	(0.002)	(0.002)	
Log of Exclusion Requests	0.00003	-0.001	0.004^{***}
(Firm)	(0.001)	(0.001)	(0.001)
Maximum Requesting Firm	-0.002	-0.009^{*}	-0.022^{***}
(Binary)	(0.005)	(0.006)	(0.007)
Log of Num Employees		0.003	0.014^{***}
(Firm)		(0.002)	(0.003)
Log Operating Revenue Turnover		-0.003	-0.011^{***}
(Firm)		(0.002)	(0.003)
2017 Unemployment Rate		-0.017^{***}	-0.018^{***}
(County)		(0.002)	(0.002)
Observations	34,552	34,552	34,552
R^2	0.218	0.220	0.496
Adjusted R^2	0.217	0.219	0.471

Note: *p<0.1; **p<0.05; ***p<0.01
Robust standard errors in parentheses

Table 13: Logistic and Probit Marginal Effects

	Dependent Variable: Exclusion Approved	
	Probit	*Logistic*
	Marginal Effects	*Marginal Effects*
	(1)	(2)
2016 Republican Share	0.072^{***}	0.059^{***}
(County)	(0.009)	(0.009)
Wave 3 or 4a	-0.210^{***}	-0.212^{***}
(Binary)	(0.007)	(0.007)
Capital End-Use	0.059^{***}	0.062^{***}
(Binary)	(0.005)	(0.005)
Industrial End-Use	0.024^{***}	0.034^{***}
(Binary)	(0.007)	(0.008)
Automotive End-Use	-0.001	-0.016^{*}
(Binary)	(0.008)	(0.009)
Other End-Use	0.120^{***}	0.141^{***}
(Binary)	(0.024)	(0.026)
Public Health Good	0.161^{***}	0.151^{***}
(Binary)	(0.017)	(0.016)
Advanced Technology	0.003	0.003
(Binary)	(0.005)	(0.005)
Log of World Imports	-0.004^{***}	-0.003^{***}
(HTSUS 10)	(0.001)	(0.001)
China's Share of Imports	0.115^{***}	0.134^{***}
(HTSUS 10)	(0.008)	(0.009)
Log of Industry Employ	0.006^{***}	0.006^{***}
(NAICS)	(0.002)	(0.002)
Log of Exclusion Requests	-0.002^{**}	0.001
(Firm)	(0.001)	(0.001)
Maximum Requesting Firm	-0.062^{***}	-0.079^{***}
(Binary)	(0.005)	(0.003)
Log of Num Employees	0.003	0.001
(Firm)	(0.002)	(0.002)
Log Operating Revenue Turnover	-0.003^{*}	-0.002
(Firm)	(0.002)	(0.002)
2017 Unemployment Rate	-0.848^{***}	-0.885^{***}
(County)	(0.132)	(0.133)
Observations	34,552	34,552
Note:		*p<0.1; **p<0.05; ***p<0.01