Section 301 and Politics: Analysis of Tariff Exclusions

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Abstract

Section 301 tariffs were imposed as a consequence of China's discriminatory business practices against American firms. However, domestic American firms who rely on Chinese imports are now faced with burdens from these tariffs. In response, affected firms were allowed to apply for exclusions for products. In this paper, we investigate the factors affecting the approval rates for these tariff exclusions. We find that an increase in county Republican vote share by 10 percentage points results in a 10% increase in probability of tariff exclusion approval.

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1 Introduction

The Trump administration began imposing a series of Section 301 tariffs on China in 2017. Consequentially, US firms are experiencing the burden from these tariffs on top of facing retaliation from the Chinese. To alleviate this tax burden, the Trump administration allowed American firms to appeal for a tariff exclusion. The approval rate across the first four waves of tariff exclusions are at 13%.

The Office of the United State Trade Representative (USTR) had authority over the appeals for tariff exclusions. The head of the USTR is a direct political appointee of the US President. In the documentation of their procedures, th 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. A July 2021 GAO report concluded that without "fully documented internal procedures, USTR lacks reasonable assurance it conducted its reviews consistently"[1]. The conglomeration of the political nature of the USTR and lack of consistencies in the process, leads us to they hypothesis that partisan politics may matter in the approval decision of a exclusion request.

Our paper investigates the political party 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 share of votes for Trump, the Republican candidate and US President during the exclusion process, in each county for the 2016 presidential election, we examine the outcomes of requests to exclude certain Chinese imports from the Section 301 tariffs. We find that a 10-percentage point increase in county Republican vote share results in an approximate 10% increase in the probability of tariff exclusion approval.

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 tax 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

[1]See GAO's Report USTR Should Fully Document Internal Procedures for Making Tariff Exclusion and Extension Decisions which is linked here https://www.gao.gov/assets/gao-21-506.pdf.

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.

The paper proceeds as follows. Section 2 describes the institutional background of the Section 301 and the exclusion process. Section 3 covers the collection of the data and the summary of the data used. Section 4 lays out our empirical methodology and identification approach. Section 5 summarizes our results. Section 6 covers threats to identification along with robustness checks. Finally, Section 7 we conclude with a discussion of future research.

2 Institutional Background

A USTR investigation in 2017 found China's trade practices unfair and harmful to the United States.[2]

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

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)[3]

[2]See Federal Register Vol. 83, No. 67, pg 14907 for details.
[3]Federal Register August 7, 2019 pg 38718

> (33) Tuners designed to clip onto musical instruments and indicate whether the instrument is in tune (described in statistical reporting number 9031.80.8085)[4]

> (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) [5]

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.

A July 2021 GAO report 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.

3 Data

The core of the data we utilize is on tariff exclusion requests and approvals. This data includes Harmonized Tariff System of the United State (HTSUS) codes at the 10-digit level, 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.

As the data from QuantGov did not include information for wave 4a. We write a R script to scrape the USTR exclusion request portal utilizing the R packages Rselenium and rvest to

[4] Federal Register March 25, 2019 pg 11157

[5] Federal Register Oct 28, 2019 pg 57807

gather information such as HTS code, requester's name, product description, and exclusion decision.[6] We then clean this data to be consistent and merge it with the data from Mercatus.

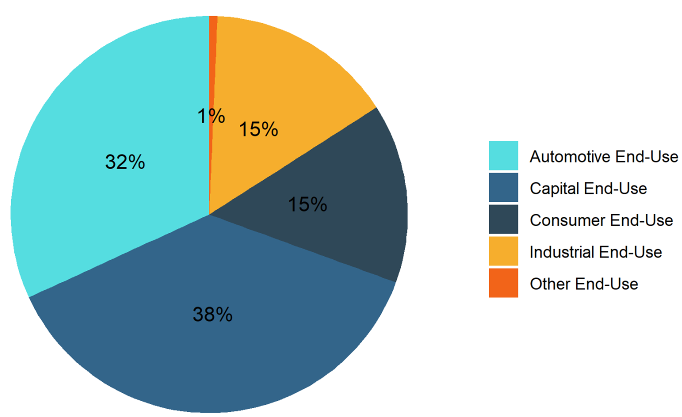
The Harmonized Tariff System of the United States (HTSUS) is a hierarchical classification system where more digits imply higher level of product detail. For example 3919101010 is defined as "Plastics and articles thereof; Rubber and articles thereof: Self-adhesive plates, sheets, film, foil, tape, strip 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[7]: 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 GAO's July 2021 report in grouping agricultural and other goods together as one group. Even with doing this 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 in Figure 1.[8]

Figure 1: Fraction of Primary End Use - By Request



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

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

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

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 were granted during the time of the pandemic, we gather this list, creating a indicator variable to be able to control for 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 put out by Census on a yearly basis which includes total Mid-March Employment by 6-digit NAICS Code. We report the distributional statistics on this in Table 1.

We use Census' US Trade Online data to gather information about imports by HTSUS 10-digit code. We gather two pieces of data from here for each code, dollar value of imports from the rest of the world and dollar value of imports from China. We also include distributional statistics on these variables in Table 1 below.

We used Orbis to gain information on firm location and other firm characteristics. The matching procedure used by Orbis rates the potential matches[9] and allows the user to review variables specific to each firm including firm location. While our primary variable of interest from Orbis is the firm location, 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. We also report distributional statistics in our summary Table 1.

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

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

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). We plot the Republican share of votes by county for 2016 in Figure 5 and 2012 in Figure 6.

We also gather data at the county level to control for local economic conditions. We gather Bureau of Labor Statistics data on 2017 county unemployment rates. We map this in Figure 8. We believe that each company's policy is determined by the 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.

4 Empirical Methodology

We estimate the following probability model to investigate the effect of Republican share of votes on the probability that a firm from that county received an exclusion approval:

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

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.

Our primary variable of interest is the 2016 share of Republican voters in county c whre firm f is located. However, this variable potentially faces endogeneity issues, even after accounting for our controls. One source of endogeneity arises from the omitted variables that might be correlated with the 2016 vote share.

While we want to allow for the potential endogeneity of our variable of interest we do not think this stems from the case of simultaneity, which we are often worried about in non-experimental design. 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 therefore employ our IV approach to account for the case of omitted variables.

The ideal instrument in our case would be a variable that is correlated with our endogenous variable of interest, 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.

We choose to employ two different instruments: 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, share of Republican voters.

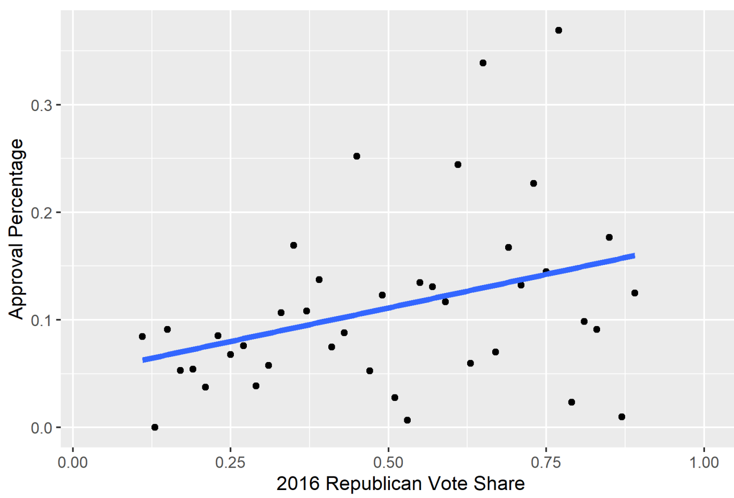
The 2012 Republican vote share could also be considered an instrument to our variable of interest because voting patterns tend to persist through time. Figure 7 shows the difference between the Republican vote shares in 2016 and 2012, and we observe that there was minimal change in voting patterns. We 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.

In further testing for the validity of our instruments, we conduct a heteroskedastic robust F-stastic on the first stage regression. 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.

5 Results

We first investigate the relationship between Republican share and approval rates. We do this by first classifying exclusion requests into bins based on the Republican vote share for the county of requesting firm. For each bin of width 2% of Republican 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%. We plot this at the midpoint of the Republican share, 47% in our example above.

Figure 2: Percentage of Exclusions Approved by Republican Share Group

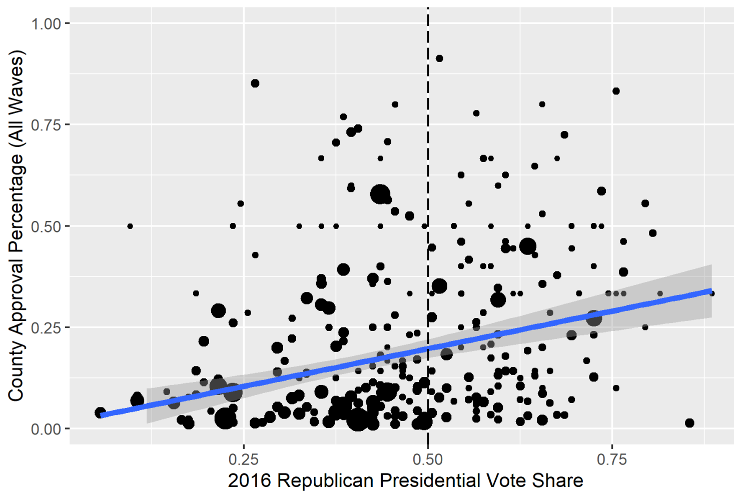


We show the positive relationship below with our classification of bins of width of 2%. While this trend is informative, the bin size is quite arbitrary, we further investigate by classifying approval rates by county.

Rates are calculated by taking the proportion of products that were approved from all the requests made for exclusions for each county. We graph the calculated approval rates against the Republican vote share, and we find that there is a positive relationship between the two variables.[10]

[10]Figure 3 in the appendix illustrates the relationship between the approval rates and 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 10, and we still observe the positive relationship.

Figure 3: Approval Rates by County



To quantify the effect of Republican vote share on the approval rates, we estimate our empirical model (as shown in equation 1). Our primary variable of interest in each model is the county share of Republican voters in the 2016 Presidential election where firm f is located. In controlling for product heterogeneity, we follow the July 2021 report from the Government Accountability Office. Our 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 the firm size, number of requests made by firm, and unemployment rates in each county.

In estimating our model, we first employ a simple linear probability model, and the results are shown in column (1) of Table 2. The results indicate that the 2016 Republican 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.

Considering the issues of endogeneity, we estimate our model with the instrumented-variable approach. Columns (2) and (3) of Table 2 shows our estimation using the instruments: share of African-Americans and 2012 Republican vote share, respectively. Qualitatively, our results do not change much. Across both the ordinary least squares and IV estimates our point estimates range from 0.09 to 0.12, while this may not seem large at surface level, when interpreting results relative to the mean approval (10% in our sample). Our interpretation is that a 10% increase in republican vote share leads to approximately an increase of 1%. Relative to the mean, this is approximately a 10% increase in approval rate.

6 Robustness

One thing we check for is nonlinearity in Republican share. This could be relevant if our story did not hold and it was more the case that they were trying to buy votes instead of rewarding their base. In this case we would observe that the relationship was actually more

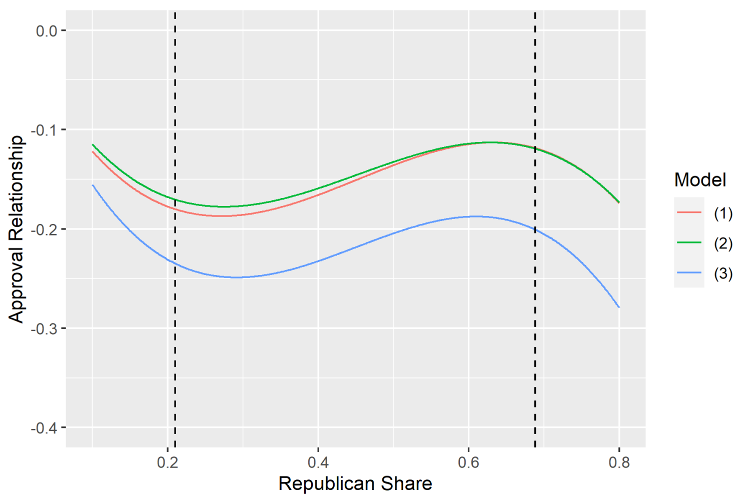
Table 2: Main Results

	Dependent Variable: Exclusion Approved		
	OLS	IV: Af Am Share	IV: Rep 2012
	(1)	(2)	(3)
2016 Republican Share	0.090***	0.117**	0.095***
(County)	(0.013)	(0.048)	(0.014)
China's Share of Imports	0.116***	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
Note:			*p<0.1; **p<0.05; ***p<0.01 Robust standard errors in parentheses

of an inverse u shape where the highest approval rates went to swing areas. We investigate this possibility a couple different ways.

We first fit a cubic function in republican share along with our set of control variables. We report full results in the Table 5. We plot the estimated relationship between Republican share and approval rate below. We also include vertical lines to denote the 5^{th} and 95^{th} percentiles of the Republican share distribution in our dataset to carve out the most relevant ranges of values. We can see that in each case a linear approximation seems to capture the relationship quite well.

Figure 4: Cubic Relationship between Republican Share and Exclusion Approval



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 share (swing areas). Allowing a different level of effect for Republican Vote Share between 48% and 52%[11]. We report results in Table 6 find that the swing range has the lowest approval rate relative to the less Republican range, however this relationship is not robust to all of our specifications. However in each specification the highest Republican Share bin holds the largest effect on Approval Rates.

7 Discussion and 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 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 Republican share into bins and estimating a

[11]We vary this range for the swing areas and find that the highest Republican Share bin continues to hold the highest level of approval.

cubic function in Republican share. In each of these cases the pattern of higher approvals for heavy Republican share counties holds.

This research will benefit from further empirical investigation that would consider other firm-specific factors, such as firm financial indicators. The specificity and level of detail in each petition could also influence the approval rates and should be addressed in future studies.

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Appendix A Data Summary and Plots

Figure 5: 2016 Republican Vote Share

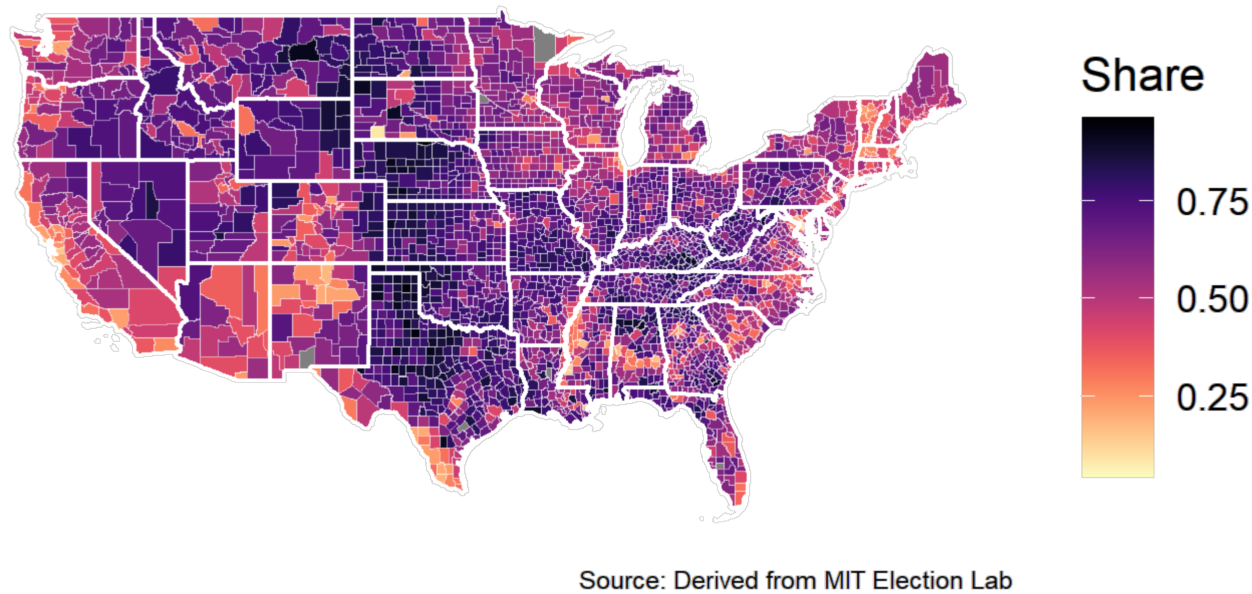


Figure 6: 2012 Republican Vote Share

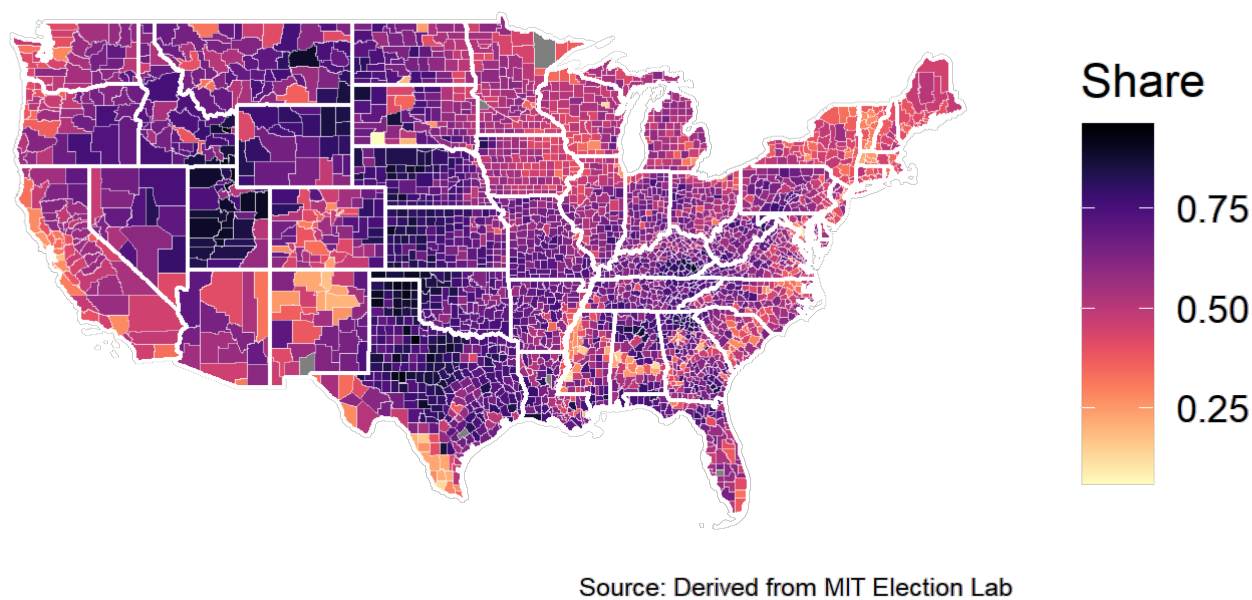


Figure 7: Difference between 2012 and 2016 Republican Vote Share

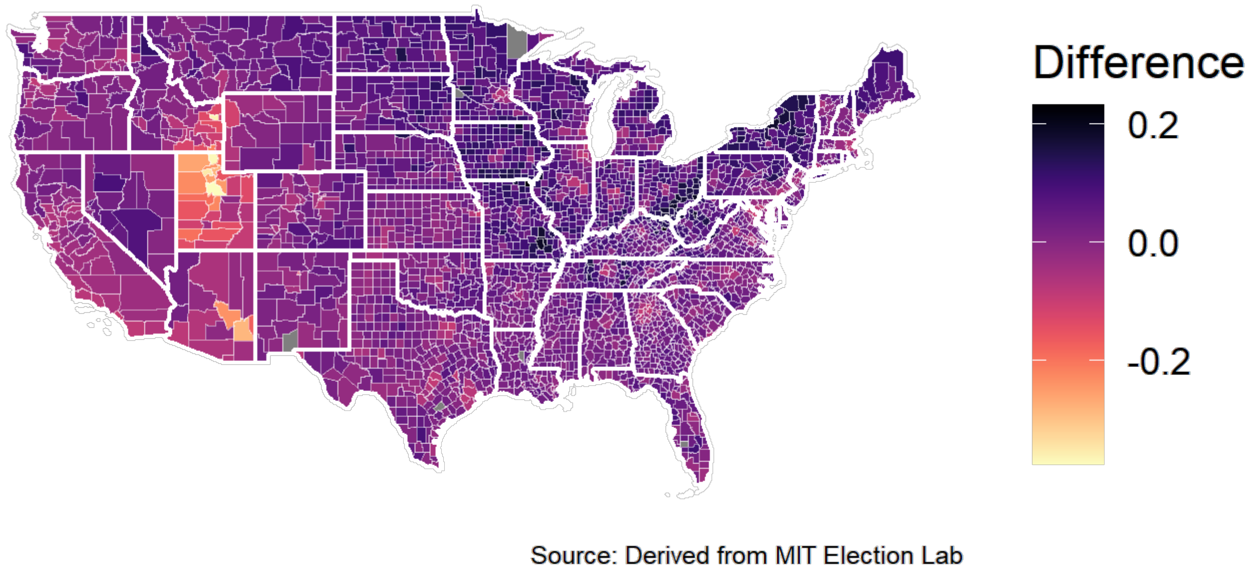


Figure 8: 2017 Unemployment Rate

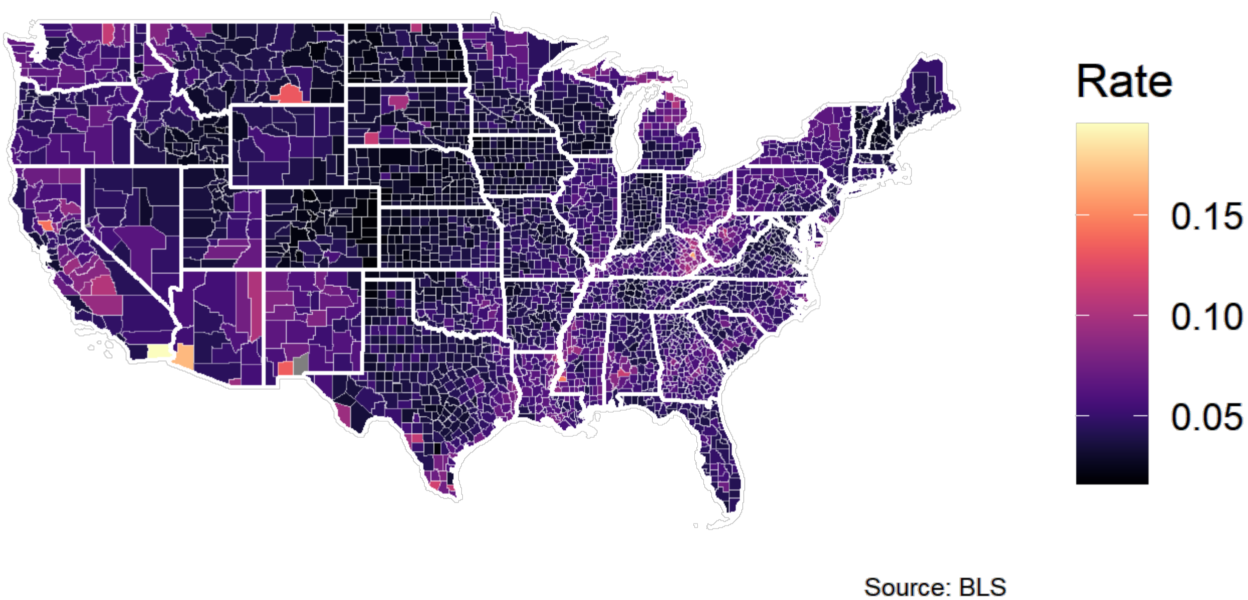
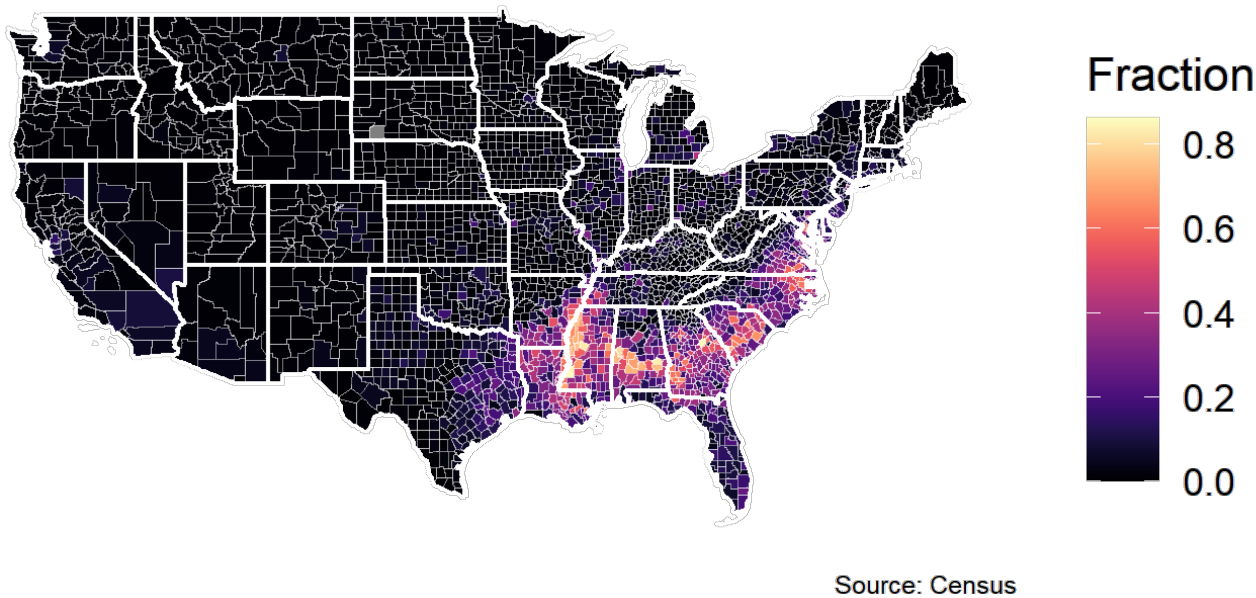


Figure 9: African American's Share of 2010 Population



Appendix B Results and Extensions

Figure 10: Approval Rate within County by Wave

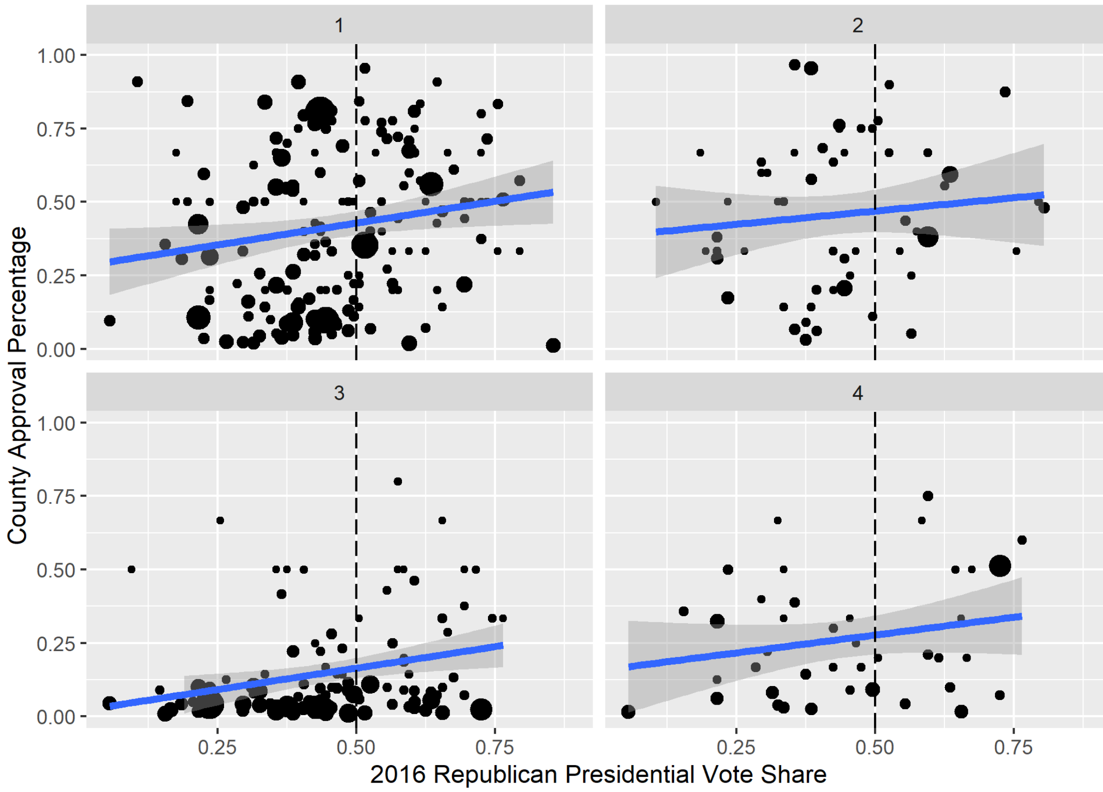


Table 3: Basic Linear Probability Models

	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 4: IV Regressions

	Dependent Variable: Exclusion Approved			
	IV: Af Am Share	IV: Af Am Share	IV: Rep 2012	IV: Rep 2012
	(1)	(2)	(3)	(4)
2016 Republican Share	0.213***	0.117**	0.131***	0.095***
(County)	(0.041)	(0.048)	(0.014)	(0.014)
Wave 3 or 4a	−0.273***	−0.282***	−0.276***	−0.283***
(Binary)	(0.006)	(0.007)	(0.006)	(0.006)
Capital End-Use	0.060***	0.060***	0.062***	0.060***
(Binary)	(0.004)	(0.004)	(0.004)	(0.004)
Industrial End-Use	0.008*	0.013***	0.012***	0.014***
(Binary)	(0.004)	(0.005)	(0.004)	(0.004)
Automotive End-Use	0.033***	0.029***	0.029***	0.028***
(Binary)	(0.005)	(0.005)	(0.005)	(0.005)
Other End-Use	0.084***	0.083***	0.081***	0.082***
(Binary)	(0.020)	(0.020)	(0.019)	(0.019)
Public Health Good	0.174***	0.169***	0.170***	0.168***
(Binary)	(0.023)	(0.023)	(0.023)	(0.023)
Advanced Technology	0.027**	0.018	0.023*	0.017
(Binary)	(0.012)	(0.013)	(0.012)	(0.013)
Log of World Import Value	−0.009***	−0.009***	−0.009***	−0.009***
(HTSUS 10)	(0.001)	(0.001)	(0.001)	(0.001)
China's Share of Imports	0.114***	0.115***	0.117***	0.115***
(HTSUS 10)	(0.008)	(0.008)	(0.008)	(0.008)
Log of Industry Employ	0.008***	0.009***	0.009***	0.009***
(NAICS)	(0.002)	(0.002)	(0.002)	(0.002)
Log of Exclusion Requests	−0.001	−0.001	−0.0003	−0.001
(Firm)	(0.001)	(0.001)	(0.001)	(0.001)
Maximum Requesting Firm	−0.014**	−0.013**	−0.006	−0.011**
(Binary)	(0.006)	(0.007)	(0.005)	(0.005)
Log of Number Employees		0.002		0.002
(Firm)		(0.003)		(0.002)
Log Operating Revenue Turnover		−0.002		−0.002
(Firm)		(0.002)		(0.002)
2017 Unemployment Rate		−0.0002***		−0.0002***
(County)		(0.00003)		(0.00002)
Observations	34,552	34,552	34,552	34,552
R^2	0.214	0.219	0.216	0.219
Adjusted R^2	0.214	0.218	0.216	0.219

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

Table 5: 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 6: Republican Share Bins

	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