The following paper was researched and written as part of LSE GROUPS 2024.

LSE GROUPS takes place during the final fortnight of the LSE Spring Term. Undergraduate students are placed in small groups; these are cross-year, interdisciplinary, and group members do not know one another in advance. Each group must then devise its own research question and carry out every stage of a small-scale research project, in less than two weeks.

LSE GROUPS is part of the LSE commitment to students learning through enquiry and developing the skills needed for knowledge creation.

The overall theme of LSE GROUPS 2024 was *Power and Politics*.

This paper was submitted on the final Thursday afternoon of the project. Students then presented their work at a conference, on the closing Friday.

More information on LSE GROUPS, and other papers.

Papers are presented as submitted by the students, without corrections.

London School of Economics and Political Science

Eden.GROUPS@lse.ac.uk

Battles Beyond Borders: Investigating the Effect of the US-China Trade War on Favourability of Trump[1]

Authors: Priyadarshan Logeswaran, Oli Kowalska Ahmed, Sophie Hau Yin Fung, Leena Safareeni, Linxuan Wang, Yilin Wang

Abstract

In 2018, the US imposed tariffs on China over multiple waves in the US-China trade war, to which China retaliated by imposing its own tariffs. By December 2018, 65.5% of US exports and 46.9% of Chinese exports were subject to trade war tariffs by the other country. Our research question aims to investigate to what extent US-imposed tariffs and retaliatory tariffs influenced voters' favourability of Trump. Using an Instrumental Variable Design with a Differences-in-Difference methodology, we find that US import tariffs significantly increased voters' cost of living; however, there were no significant changes in voters' favourability of Trump. Instead, favourability is better explained by prior foreign policy stances and/or actions by Trump in 2016. Next, we use a Krugman Model of International Trade to analyse the effects of retaliatory tariffs. We mathematically show that the average cost of agricultural producers increases, theoretically resulting in an exit of producers from the industry and greater unemployment. However, the introduction of large protectionist subsidies negated the theoretical effects established in our model, demonstrating political intent by Trump to protect his favourability. These findings demonstrate the trend that we are likely to observe should Trump come to power in the 2024 US presidential elections and impose his proposed tariffs. Our research is the first to suggest the above mechanisms through which the trade war impacted Trump's favourability.

Key words: *Trade war, Trump, favourability, tariffs, international trade*

---

[1] Acknowledgements: We would like to give special thanks to LSE Eden Centre and LSE LIFE, for their support; Haoran Shi, Department of Psychological and Behavioural Science, LSE, for his supervision and patience with this research project; Michael Gmeiner, Assistant Professor of Economics (Education), Department of Economics, for his help on our methodology; Dr Ellis Saxey, for teaching

Introduction

In 2018, the US and China entered a trade war, with the USA imposing 25% tariffs on $50 billion worth of Chinese imports and additional 10% tariffs on $200 billion, which later increased to 25%; China retaliated with equivalent tariffs on US imports (Liu, 2018).

Academic literature primarily focuses on the impact of Chinese retaliatory tariffs on US outcomes (Chyzh & Urbatsch, 2021; Blanchard et al., 2024; Fetzer & Schwartz, 2021; Kim & Margalit, 2021); we bridge this gap by directly focusing upon the effect of US-imposed tariffs on the favourability of Trump. This is important as Trump has announced a 60% blanket tariff on imports from China for the upcoming 2024 Presidential election (Wolff, 2024), and voter attitudes towards his proposed tariffs will heavily influence economic outcomes for the US throughout Trump's presidential term should he come to power. We also establish a missing link that literature on Chinese retaliatory tariffs does not capture; that is, how would the favourability of Trump have differed if protectionist subsidies were not rolled out to agricultural producers.

Firstly, we analyse the political aftershock from US imposed tariffs on China on voters' favourability. We establish a causal chain using an instrumental variable and a differences-in-difference design. We show the importance of time trends over the introduction of tariffs by Trump in explaining the decline in favourability towards Trump, utilising ANES survey data, where favourability is measured using a feelings thermometer. Secondly, we aim to analyse the effect of Chinese retaliatory tariffs. Focusing on the agricultural industry within the US, we use a modified Krugman model to show the effect of tariff introduction. We show that the number of US firms theoretically decreases. Our analysis reveals the motivation for Trump's protectionist subsidies towards the agricultural sector as a response to the retaliatory tariffs.

1. Literature Review

Tariffs influence electoral support through countless mechanisms. Literature has shown that protectionist sentiments have grown in the US since the start of the century; Trump's 2016 electoral victory has been partially attributed to rising Chinese competition spurring protectionist sentiments among voters, especially in key battleground states, such as Pennsylvania, Michigan, and Wisconsin (Autor et al., 2017). Therefore, the increase in US-imposed tariffs in 2018, which reduced Chinese import competition (Zheng et al., 2022); this raised Republican electoral support in protected counties during the 2018 mid-election, as demonstrated by Li et al. (2019).

The economic impact of tariffs in international trade has attracted much academic attention; it suggests strong economic mechanisms underlying the link between tariffs and the favourability towards the incumbent. For instance, import tariffs lead to increased costs of production in the long run (Huang, 2023), lowering domestic employment and triggering significant relocation of global trade (Fajgelbaum et al., 2020). Higher prices of imports immediately heighten the cost of living and lowered welfare, which in the case of the USA, led to an estimated cumulative deadweight welfare loss of approximately $8.2 billion in 2018 due to tariffs imposed on China (Amiti et al., 2019).

On the other hand, tariffs imposed by other countries damage domestic industries and the incumbent's favourability. As these tariffs increase, corporations seek to offshore production overseas to avoid the cost of additional tariffs, resulting in an increase in domestic unemployment (Rickard, S. J., 2022). In the US-China trade war, Waugh (2019) estimated that agricultural and manufacturing employment growth after Chinese retaliatory tariffs to be 1.70% lower in counties that are exposed by a higher proportion to foreign tariffs. This is considered a relatively small impact given the size of the tariffs. Those suffering from unemployment due to offshoring experience significantly greater financial difficulties (Epstein et al., 2014). This reduced their favourability of Trump (Bachmann & Braun 2011; Görg & Hanley 2005). Indeed, counties most affected by Chinese retaliatory tariffs experienced declines in the Republican vote share in the 2018 mid-election (Blanchard et al., 2024; Fetzer & Schwartz, 2021; Kim & Margalit, 2021).

According to prior literature, we hypothesized that: H1: The change in the cost of living due to US-imposed tariffs and rising import expenditure led to a reduction in voters' favourability of Trump.

H2: Chinese retaliatory tariffs should result in a significantly higher number of firms forced to exit their industries in the US had protectionist subsidies not been introduce

2. Method

2.1 US-imposed tariffs on China

2.1.1 Data

Check appendix 2

2.1.2 Method

[Appendix 2.1.2.a shows why a regular OLS regression would not work]

We first analyse the effect of US-imposed tariffs on the favourability of Trump using an Instrumental Variables (IV) with a Differences-in-Difference (DD) design. We assume that the US-imposed tariffs are exogenous, as there was no expectation of the implementation of the tariffs (Amiti et al, 2019). We use the IV of average import expenditures by state from China, where we construct a causal chain suggesting that the increase in the cost of importing from China due to the introduction of tariffs directly led to an increase in the average consumption expenditure across states, implying an increase in the cost of living. We hypothesize that this change in consumption expenditure led to a reduction in favourability of Trump.

The DD estimation uses the IV to exploit the differential increase in consumption expenditure across different states — states that imported a higher quantity of products from China (due to being larger in size, or other relevant reasons) would have suffered a larger change in consumption expenditure from the tariff. Our treatment is continuous, not binary. Hence, we test whether states with larger changes in consumption expenditure changed their favourability of Trump by a significantly higher proportion than the states that experienced smaller reductions in the quantity of imports. This is representative of the reduced form of our final regression.

The regression specifications are as follows:

First Stage:

$$ConsExp_{i,t} = \beta_0 + \beta_1 ImportExp_{i,t} + \beta_2 GDPgr_{i,t} + \beta_3 Jobprop_{i,t} + \gamma_i + \delta_t + \varepsilon$$

Second Stage:

$$VoterFav_{i,t} = \alpha_0 + \alpha_1 \widehat{ConsE}xp_{i,t} + \alpha_2 GDPgrow_{i,t} + \alpha_3 JobProp_{i,t} + \gamma_i + \delta_t + \epsilon_i$$

All variables above are in logarithm terms. In the first stage, we regress state-level consumption expenditure $ConsExp_{i,t}$ on state-level import expenditure from China $ImportExp_{i,t}$ to find the fitted values $\widehat{ConsE}xp_{i,t}$. Then, we regress state-level favourability of Trump $VoterFav_{i,t}$ on $\widehat{ConsE}xp_{i,t}$ in our second stage. We include state-level GDP growth $GDPgrow_{i,t}$, and state-level proportion of US jobs $JobProp_{i,t}$ in both stages to account for any confounding variation that may be created by the two variables. We conduct Hausmann tests on confounding variables and show these are good controls. We include state fixed effects [2]γ_i and time fixed effects[3] δ_t to account for any state and time invariant factors between the two periods. Standard errors ε are robust.

[In appendix 2.1.2.b, we show that the assumptions for DD and IV are fulfilled.]

2.2 Chinese Retaliatory Tariffs

2.2.1 Setup of Model

In this section, we analyse the effect of Chinese retaliatory tariffs on the US on the favourability of Trump. Proving a causal effect using this chain is empirically difficult. This is due to two reasons. Firstly, Chinese retaliatory tariffs were accompanied by retaliatory tariffs by the other nations, such as the EU, India and Russia (International Trade Administration, 2023). Literature shows that there is a lagged supply-side response by US firms, implying that the economic response of US firms concerned all retaliatory tariffs, not just China (Zeng, 2023), making it difficult to isolate a causal chain using Chinese retaliatory tariffs only.

Secondly, Trump provided large subsidies to heavily affected sectors, especially the agricultural sector. Subsidies by the federal government to farmers increased by approximately $9 billion in 2019, and $23 billion in 2020 (Economic Research Service, 2024). Thus, empirical estimation will

---

[2] State-fixed effects: time-invariant effects of states (for example: size). If it's correlated with a regressor, then it induces bias as a confounder. By controlling for them, we remove time-invariant endogeneity across states.

[3] Time-fixed effects: the difference in demographics within states across time. By controlling for them, we remove the time trend effects between 2016 and 2018 across the same state.

underestimate the true effects and hide the mechanisms that a pure causal chain studying the effect of Chinese retaliatory tariffs on economic outcomes and the favourability of Trump may show.

Hence, we aim to analyse the impact of Chinese retaliatory tariffs by mathematically modelling industry-level responses to the tariffs. We combine existing literature with a Krugman Model of International Trade (KMIT) (New Trade Model). The KMIT utilizes New Trade Theory, pioneered by Paul Krugman (The Library of Economics and Liberty); we model the US and China as two countries with similar factor endowments and technologies. In this model, industries engage in monopolistic/imperfect competition.

This model requires that industries within both countries fulfil three assumptions: increasing returns to scale (IRS), differentiation of goods and many firms within the industry. We demonstrate that these assumptions are fulfilled by restricting our analysis the agricultural sector in the US by using existing literature. For further details, see appendix 2.2.1.a.

The KMIT has two equations/curves that determine outcomes in our stylized monopolistic competition world. The two curves below are similar to a Demand and Supply curve, although not the same.

First, we have the PP curve, which shows average price as a function of the number of firms in the agricultural industry:

$$P = c + \frac{1}{bn}$$

shows marginal costs for all firms within the industry; it is assumed that is constant across all firms. refers to the weighted average price elasticity of demand for agricultural products.

On the other hand, we have the CC curve, which shows average cost as a function of the number of firms in the agricultural industry:

$$AC = c + \frac{nF}{S}$$

refers to the fixed cost of entering the agricultural industry, such as the upfront costs of setting up a farm and purchase of required capital such as machinery. refers to the total market size of the agricultural industry in the USA.

The derivations of the two functions above are shown in appendix 2.2.1.b.

2.2.2 Model Method

Under this model, we show the effects of introducing Chinese retaliatory tariffs. We introduce a tariff t in the Total Cost function TC . This is motivated by Amiti et al. (2019); they stated that the cost of the tariff was partially passed on to US exporters, with an aggregate cost of \$2.4 billion. The parameter of interest is n .

$$TC = F + cQ + tQ$$

$$AC = \frac{F}{Q} + c + t$$

Using the Symmetric Equilibrium condition (justified in the appendix)

$$Q = \frac{S}{n}$$

We substitute the function above in the AC function

$$AC = \frac{nF}{S} + c + t$$

This represents our new AC function. Under the assumption that all firms aim to maximize profits, we solve the equilibrium condition below where average price equals to average cost at the industry level. Note that b, F and S are fixed in the short run.

$$P = AC$$

$$c + \frac{1}{bn} = c + \frac{nF}{S} + t$$

$$\frac{1}{bn} = \frac{nF}{S} + t$$

$$S = n^2(bF) + n(bSt)$$

$$(bF)n^2 + (bSt)n - S = 0$$

Using the quadratic formula:

$$n = \frac{-bSt + \sqrt{(bSt)^2 + 4bFS}}{2bF}$$

3. Findings

3.1 US-Imposed Tariffs

This study tests the null hypothesis that an increase in consumption expenditure has no effect on favourability of Trump. To examine this, we conducted two two-stage least squares (2SLS) regressions of favourability towards Trump on consumption expenditure, using US imports from China as an instrument for consumption expenditure. In the first regression, we controlled for time-fixed effects and did not for the other regression.

First, we will compare findings from the regressions on Trump's favourability on fitted values of consumption expenditure, using state-level imports from China as an instrument.

Table 1: First Stage

	Consumption Expenditure	Consumption Expenditure
Import Expenditure	0.270** (0.101)	0.470*** (0.089)
State Fixed Effects?	Yes	Yes
Time Fixed Effects?	No	Yes

Table 1 shows our first stage regression, including and excluding time-fixed effects. Both regressions give positive and significant estimates of the effect of total consumption expenditure on US imports from China, satisfying the relevance assumption needed to use Chinese imports as an instrument for total consumption expenditure.

Table 2: Second Stage

	Favourability of Trump	Favourability of Trump
Import Expenditure	-2.219** (0.832)	-0.002 (0.101)
State Fixed Effects?	Yes	Yes
Time Fixed Effects?	No	Yes

Table 2 shows our second stage results. When time-fixed effects are not controlled for, a 1% increase in total consumption expenditure is on average associated with a 2.219% decrease in Trump's favourability, *ceteris paribus*. This estimate is significant, with a p-value of 0.028. However, once we control for time-fixed effects, as shown in Table 3, all significance disappears; 1% increase in total consumption expenditure is on average associated with 0.002% decrease in Trump's favourability, *ceteris paribus*.

Therefore, we fail to reject our null hypothesis; there is insufficient evidence to suggest a causal effect on Trump's favourability due to the US-imposed tariffs on imports from China. The stark contrast between the estimates in Table 2 shows that the inclusion of time-fixed effects significantly alters the results.

[Full Stata code and Stata-generated regression tables can be found in Appendix 3.1]

4. Discussion

4.1 US-Imposed Tariffs

Our results suggest that there are unobserved factors due to time-trends which primarily explain the decline in favourability towards Trump; these trends were likely established during his 2016 presidential campaign. There are two driving reasons for this: firstly, Trump announced his tariff policy towards China during his 2016 campaign (Needham 2016). Secondly, Trump was involved in many controversies in 2016; an example includes widespread criticism from within his own party for questioning the ability of a federal judge of Mexican descent to fairly preside over a fraud lawsuit against his now-defunct real estate investment course known as Trump University (McCammon, 2016).

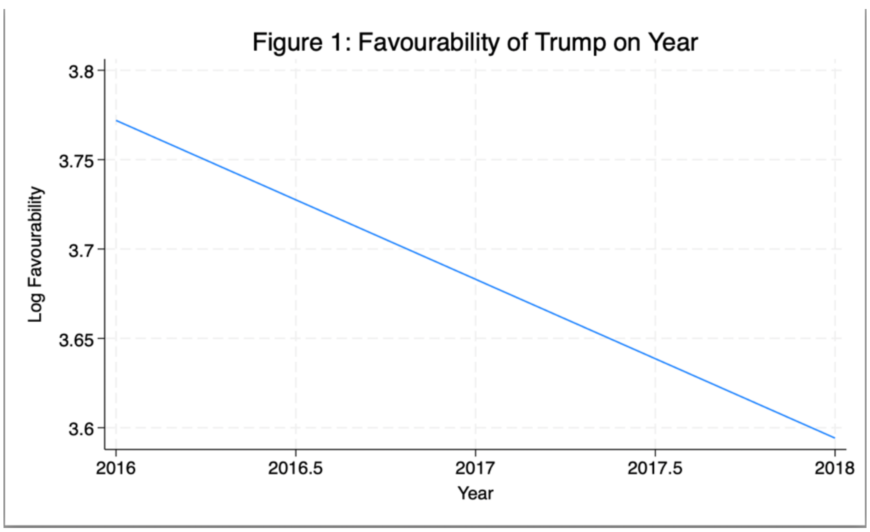

Figure 1: See Appendix 4.1 for Stata code

Hence, the downward trend in public favourability towards Trump followed a trajectory as voters likely made up their opinions on Trump; according to our findings, any controversial foreign policy action and the start of the trade war in 2018 perfectly fit voters' expectations, thereby not marginally changing their favourability of Trump over the course of Trump's term.

4.2 Chinese Retaliatory Tariffs

There is a strictly negative relationship between n and t ; the introduction of a tariff will always reduce the number of firms in the agricultural industry in this model. We graphically show this by illustrating a parallel shift in the CC curve in an Average Price/Cost vs Number of Firms graph. In the appendix, we construct a hypothetical scenario that shows exactly the change illustrated below.

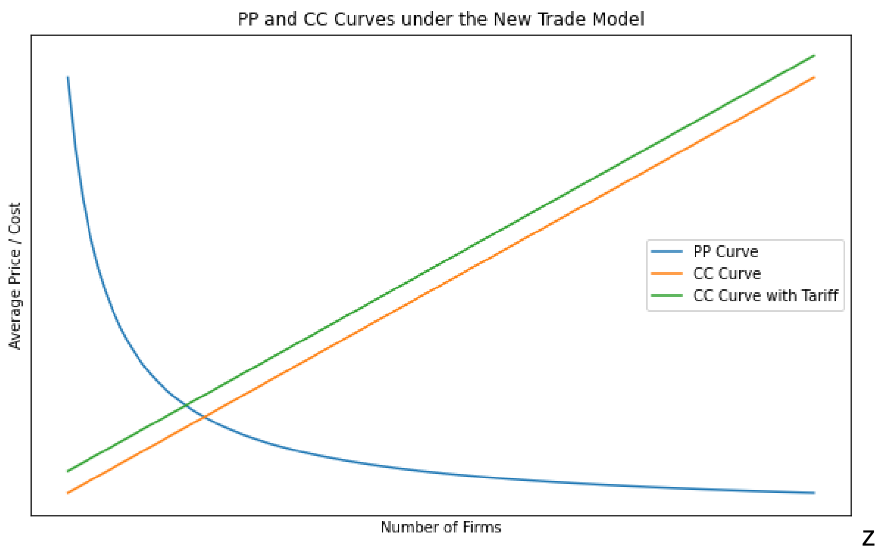

Figure 2: See Appendix 4.2 for python code.

In the absence of any corrective measures by the Trump and the US government, this is the expected impact on the agricultural sector. We argue that this is the primary mechanism through which short-term unemployment would be created; farms or other entities within the agricultural sector exit the market due to the higher average cost of production. Those who exit are usually the least productive or can offshore agricultural production to neighbouring countries.

This underlines Trump's intent for the introduction of higher subsidies, and the drive in expansionary fiscal policy by the US government. These measures cancel out t in our AC equation. While we did observe insignificant effects of US-imposed tariffs on China in our first analysis, we argue that an increase in the cost of living has a less tangible effect on livelihoods than the unemployment that would have created by Chinese retaliatory tariffs. Literature has shown that mental health indicators deteriorate significantly more with an increase in unemployment than the cost of living; we can extend this analysis to the current scenario (Pappas, 2020). Had corrective policies not been introduced, we hypothesize that this would have significantly reduced favourability of Trump, as the economic impacts on the US economy would have been far more disastrous than the increase in the cost of living shown in our first analysis.

5. Limitations

5.1 US-Imposed Tariffs on China

The primary limitation with the DD analysis is the low sample size of competitive states; there are only 12. However, standard errors are small, which helps achieve significance in our findings.

Data is only available on the favourability of Trump in 2016 and 2018 at the state level; hence, our analysis is limited in terms of its granularity. However, this data is available at the county level at regular time periods between 2016 and 2018. However, given the report's word and time constraints, a county-level analysis is extremely difficult.

5.2 Chinese Retaliatory Tariffs on US

The primary limitation of the Krugman Model is its simplified nature. The assumption of constant marginal costs c may not be fulfilled, and firms may not be profiting maximizers. Further, factor endowments and technologies may be different between the US and China.

However, despite the simplifications, we argue that there is much to be learned from utilizing this model. By restricting our analysis to the agricultural sector, the above limitations can be relaxed although not completely eliminated. This is because we expect firms within the agricultural sector to be reasonably similar to one another, and we do not expect large differences in production technologies between the US and China in technologies.

6. Conclusion

To conclude, we find no statistically significant effect of US-imposed tariffs on favourability of Trump. Instead, we suggest that the observation in the decrease of favourability is due to time trends which were pre-determined in Trump's 2016 presidential campaign. In addition, we propose that the Chinese retaliatory tariffs would have detrimental impacts on favourability of Trump had he not introduced protectionist subsidy.

We use our findings above to provide expectations for 2024 US presidential elections. For context, Trump has pledged to impose large additional tariffs if he is re-elected, with a 60 percent tariff on Chinese goods and a 10 percent tariff on products from other countries (Wolff, 2024).

As suggested by Li (2020) and as shown in our first stage regression analysis, additional tariffs will clearly decrease welfare in the US and hurt economic outcomes. However, we do not expect this to differentially reduce favourability of Trump. Jackson and Newall (2024) suggest that recent trends of voter opinions of Trump seem to be unaffected by the guilty verdict on 34 felony counts of falsifying business records, even though two-thirds of Americans believe that the verdict was correct (Ipsos, 2024). This mirrors our findings on favourability of Trump from the trade war; except in this case, time trends reflect a larger favourability of Trump. The driving reasons for this in 2024 is beyond the scope of our study; however, we expect that this is because of recent US foreign policy stances with the Israel-Palestine war and a social media war in the run-up to the 2024 presidential elections.

By extension, if tariffs are introduced by Trump should he come to power, China will likely retaliate with similar political targeting as observed in 2018. The pattern of subsidy provision and expansionary fiscal policy must continue if Trump chooses to preserve his favourability, especially since the US cannot afford to have mass unemployment from a trade war post-COVID. However, the current federal government budget deficit is enormous, with the 2024 year-to-date shortfall reaching $1.2 trillion (Cang & Zhou, 2024). The federal government may be constrained if it chooses to use a mass protectionist subsidy approach. (See appendix 6 for further research recommendations).

Appendix

Appendix 2.

2.1.1.a

<u>Data</u>

We use annualised data compiled from International Trade Association, 2024; American National Election Studies [ANES], 2019; American National Election Studies [ANES], 2016; (BEA Interactive Data Application, n.d.); World Integrated Trade Solution, 2016; Bown, 2023 and Election 2016: Results by State, 2017.

Using 2016 presidential election voting data ("Election 2016: Results by State," 2017), we selected a sample of competitive swing states, limiting the difference between votes for Trump and Hillary Clinton to 5%. This controls for pre-existing strong beliefs and biases for/against Trump, therefore minimizing the skew in our results since it makes the states in our sample more similar and thus gives a more unbiased estimate for the effect of the introduction of US-imposed tariffs on Trump's favourability.

We collected data on Trump's favourability using a "feelings thermometer" measure included in our election data (ANES, 2019; ANES, 2016).

We collected data on total consumption expenditure (BEA Interactive Data Application, n.d.). This data is presented in real dollar value amounts.

We also collected data on the dollar value of imports from China for each state in our sample (International Trade Association, 2024). We constructed our "imports from China" variable by calculating the proportion of each state's imports from China relative to the total imports from China into the US.

We also collect data on GDP growth per state and each state's proportion of total US jobs (U.S. Bureau of Economic Analysis, 2024) to use as controls in our regression analysis. GDP growth by state reflects changes in economic performance, and each state's proportion of US jobs accounts for changes in Trump's favourability resulting from fluctuations in unemployment between 2016-2018.

After plotting the raw data of favourability of Trump against total consumption expenditure, we observe a logarithmic trend. Therefore, all our variables are log-linearized to fit our data better.

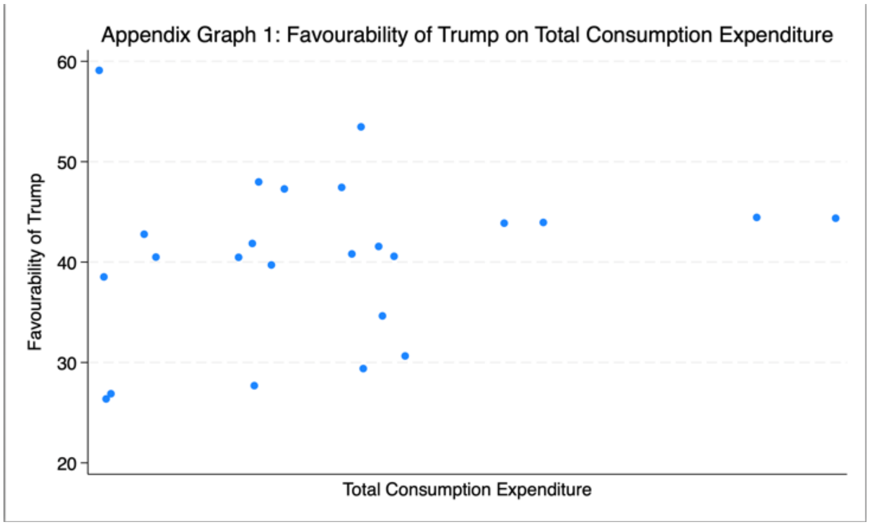

Figure 3: See Appendix 2.1.1.b for Stata code

Stata code for generating graph

```
twoway scatter fav totalPCE
```

*totalPCE is our variable for consumption expenditure

2.1.2.a

Addressing the above question using a regular OLS will not yield accurate results. The main limitation of this approach is endogeneity, caused by other confounding economic and foreign policy stances that Trump endorsed during the same period. This includes tensions worsening throughout 2017 with the DPRK and the Middle East (specifically Iran, where Trump accused Iran of destabilizing the Middle East). A majority of the US population was critical of Trump's actions; this would contribute to an overestimation of a decline in voter favorability in an OLS regression.

2.1.2.b

The DD estimation method requires two assumptions to be fulfilled. Firstly, parallel trends must exist between states in terms of voter favourability for Trump. Since we are using a two-way fixed effects interpretation of the DD estimation method, we can relax the requirement of parallel trends as we control for state fixed effects and time fixed effects.

Secondly, there must not be other exogenous shocks that occur at the same time as the US Tariffs on China. There is a lag in response to the tariffs from stakeholders such as multinational corporations (MNCs) and workers; this delayed any supply-side responses to the tariffs (Zeng, 2023). Hence, all immediate shocks originate from the demand side; Amiti et al. (2019) also shows there was an almost instant change in prices due to tariffs, implying that our variables of interest likely changed quickly. This satisfies our second assumption.

Further, the IV must satisfy three conditions to be valid: relevance, exogeneity, and random assignment. Proving relevance involves running a first-stage regression, which is shown in our findings. Secondly, exogeneity requires that only affects through the channel described above and is uncorrelated with any other factors affecting voter favourability. We argue that this is fulfilled by restricting our analysis to 'competitive' states[4], as the confounding political bias channel is eliminated on an aggregate level. Lastly, random assignment is fulfilled, as the tariffs implemented reliably within the first wave are reliably random (Amiti et al., 2019). We also use state fixed effects to help eliminate differences across states, such as unobserved political bias and other endogenous factors.

2.2.1.a

Kim and Margalit (2021) show that China politically targeted industries in Republican-leaning counties; one of the major industries within such counties is the agricultural industry. For the sake of simplicity, the agricultural industry also cleanly fulfils the assumptions required by the Krugman Model, making it ideal for this analysis.

Firstly, evidence has shown that the US agricultural industry exhibits significant IRS, due to high levels of public research investment and learning-by-doing (Yang & Shumway, 2020). Secondly, goods produced in the industry are horizontally differentiated, with farms' production ranging from livestock, including meat and poultry, to crops, such as corn and soybeans (Economic Research Service, 2024). Thirdly, there are over 2 million farms that compete with one another in the USA (National Agricultural Statistics Service, 2019). Although farms are not exclusively the only type of firm in the agricultural sector, it is the simplest metric of the number of firms and hence competitiveness. All assumptions are fulfilled.

2.2.1.b

i) PP curve derivation

The demand function is:

$$Q = S\left(\frac{1}{n} - b\left(P - \overline{P}\right)\right)$$

[4] Refer to appendix 2 for the definition of competitive states.

Rearranging this equation gives us:

$$P = \overline{P} + \frac{1}{bn} - \frac{Q}{bS}$$

Taking the First Order Condition and finding MR :

$$MR = P - \frac{Q}{bS}$$

Where MR refers to the marginal revenue.

Since firms maximize profits, $MR = c$

$$c = P - \frac{Q}{bS}$$

Using the symmetric equilibrium condition where $Q = \frac{S}{n}$

$$P = c + \frac{1}{bn}$$

ii) CC curve derivation

$$TC = F + cQ$$

$$AC = \frac{F}{Q} + c$$

Using the Symmetric Equilibrium condition

$$AC = \frac{nF}{S} + c$$

Appendix 3.

3.1

Full Stata code:

```
drop if missing(log_import, log_govexpend, log_inflation, log_gdpgrowth)


egen post = anymatch(year), values(2018)

gen postlogcons = log_total_cons*post

gen postlogchinaim = log_chinaimports*post

gen postlogrowim = log_rowimports*post



*second stage - ivregress 2sls with time FE for china vs row
xi: ivregress 2sls log_fav log_gdpgrowth log_jobsprop (postlogcons = postlogchinaim) i.state_num i.year, robust cluster(state_num)
etable, title("Table 3: Instrument is Chinese Imports + Time FE ")


**second stage - ivregress 2sls withOUT time FE for china vs row
xi: ivregress 2sls log_fav log_gdpgrowth log_jobsprop (log_total_cons = log_chinaimports) i.state_num, robust cluster(state_num)
etable, title("Table 4: Instrument is Chinese Imports + No Time FE ")


// first stages
*with time FE
xi: reg postlogcons postlogchinaim log_gdpgrowth log_jobsprop i.year i.state, robust
etable, title("Table 1: First stag regression + Time FE ")
*without time FE
xi: reg log_total_cons log_chinaimports log_gdpgrowth log_jobsprop i.state, robust
etable, title("Table 2: First stage regression + No Time FE ")

// Step 2: Verify the data
browse
describe

rename A state
rename B year
rename C rpp
rename D import
rename E govexpend
rename F inflation
rename G gdpgrowth
rename H totalPCE
rename I tarrifs
rename J fav
rename K jobs
rename L jobsprop
rename M rowimports
rename N rowimportsprop
rename O chinaimports
rename P chinaimportsprop

encode state, gen(state_num)


destring inflation, replace ignore(",") force
destring gdpgrowth, replace ignore(",") force

destring chinaimportsprop, replace ignore(",") force
destring rowimportsprop, replace ignore(",") force



misstable summarize rpp import govexpend inflation gdpgrowth totalPCE

sort state_num


xtset state_num year


// Log transformation
gen log_import = log(import)
gen log_govexpend = log(govexpend)
gen log_inflation = log(inflation)
gen log_gdpgrowth = log(gdpgrowth)
gen log_tariffs = log(tarrifs)
gen log_total_cons = log(totalPCE)
gen log_fav = log(fav)
gen log_jobs = log(jobs)
gen log_jobsprop = log(jobsprop)
gen log_rowimports = log(rowimports)
gen log_rowimportsprop = log(rowimportsprop)
gen log_chinaimports = log(chinaimports)
gen log_chinaimportsprop = log(chinaimportsprop)
```

First-stage regression (including time fixed effects) Stata-generated regression table:

```
i.year           _Iyear_2016-2018     (naturally coded; _Iyear_2016 omitted)
i.state          _Istate_1-12         (_Istate_1 for state==Arizona omitted)

Linear regression                                Number of obs     =         24
                                                 F(15, 8)          =    1823.93
                                                 Prob > F          =     0.0000
                                                 R-squared         =     0.9995
                                                 Root MSE          =     .25915
```

postlogcons	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
postlogchinaim	.4702441	.0885427	5.31	0.001	.2660642	.6744239
log_gdpgrowth	-.1940812	.065691	-2.95	0.018	-.3455651	-.0425974
log_jobsprop	6.6593	4.379956	1.52	0.167	-3.440898	16.7595
_Iyear_2018	9.741872	.7771323	12.54	0.000	7.949802	11.53394
_Istate_2	-7.471245	5.035576	-1.48	0.176	-19.0833	4.140813
_Istate_3	-3.562958	2.114003	-1.69	0.130	-8.437857	1.311942
_Istate_4	9.639533	6.486149	1.49	0.176	-5.317554	24.59662
_Istate_5	-3.208852	1.846759	-1.74	0.120	-7.467485	1.049781
_Istate_6	-.5597569	.1888449	-2.96	0.018	-.995234	-.1242797
_Istate_7	4.51362	3.289099	1.37	0.207	-3.071056	12.0983
_Istate_8	8.947062	6.25292	1.43	0.190	-5.472199	23.36632
_Istate_9	-3.300262	2.012955	-1.64	0.140	-7.942145	1.34162
_Istate_10	-4.994307	3.143517	-1.59	0.151	-12.24327	2.254656
_Istate_11	-2.377561	1.478668	-1.61	0.147	-5.787377	1.032255
_Istate_12	-.4249017	.1514539	-2.81	0.023	-.774155	-.0756485
_cons	25.94542	17.21346	1.51	0.170	-13.74889	65.63973

First-stage regression (excluding time fixed effects) Stata-generated regression table:

```
i.state          _Istate_1-12         (_Istate_1 for state==Arizona omitted)

Linear regression                                Number of obs     =         24
                                                 F(14, 9)          =     767.59
                                                 Prob > F          =     0.0000
                                                 R-squared         =     0.9980
                                                 Root MSE          =     .05695
```

log_total_cons	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
log_chinaimports	.270043	.1008302	2.68	0.025	.0419492	.4981367
log_gdpgrowth	.0033887	.0390587	0.09	0.933	-.0849683	.0917456
log_jobsprop	1.320369	.6645444	1.99	0.078	-.1829346	2.823673
_Istate_2	-.7035647	.6758961	-1.04	0.325	-2.232548	.8254184
_Istate_3	-.7838115	.2466232	-3.18	0.011	-1.341712	-.2259109
_Istate_4	1.064313	.8882888	1.20	0.261	-.9451358	3.073762
_Istate_5	-.4278721	.2097893	-2.04	0.072	-.9024484	.0467042
_Istate_6	-.3988879	.1677982	-2.38	0.041	-.7784738	-.019302
_Istate_7	.0640633	.5245821	0.12	0.905	-1.122624	1.25075
_Istate_8	.8538405	.916467	0.93	0.376	-1.219352	2.927033
_Istate_9	-.5885762	.2383056	-2.47	0.036	-1.127661	-.0494915
_Istate_10	-.6352421	.3736304	-1.70	0.123	-1.480453	.2099686
_Istate_11	-.3695631	.1726031	-2.14	0.061	-.7600184	.0208923
_Istate_12	-.3229967	.1243201	-2.60	0.029	-.6042282	-.0417652
_cons	16.96669	3.27685	5.18	0.001	9.553945	24.37944

Second-stage regression (including time fixed effects) Stata-generated regression table:

```
i.state_num       _Istate_num_1-12    (naturally coded; _Istate_num_1 omitted)
i.year            _Iyear_2016-2018    (naturally coded; _Iyear_2016 omitted)

Instrumental variables 2SLS regression          Number of obs   =         24
                                                Wald chi2(15)   =      21.09
                                                Prob > chi2     =     0.1340
                                                R-squared       =     0.8858
                                                Root MSE        =     .06997

                               (Std. err. adjusted for 12 clusters in state_num)
```

log_fav	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
postlogcons	-.002002	.1014351	-0.02	0.984	-.2008111	.1968071
log_gdpgrowth	.0576292	.0700019	0.82	0.410	-.0795719	.1948303
log_jobsprop	3.932894	1.618139	2.43	0.015	.7613998	7.104389
_Istate_num_2	-4.598134	1.830647	-2.51	0.012	-8.186137	-1.010131
_Istate_num_3	-1.948162	.7850521	-2.48	0.013	-3.486836	-.4094885
_Istate_num_4	5.946979	2.341485	2.54	0.011	1.357752	10.53621
_Istate_num_5	-1.771173	.7414689	-2.39	0.017	-3.224425	-.3179206
_Istate_num_6	-.0708194	.0880305	-0.80	0.421	-.2433561	.1017172
_Istate_num_7	2.776222	1.170254	2.37	0.018	.4825664	5.069877
_Istate_num_8	5.183577	2.233417	2.32	0.020	.8061591	9.560995
_Istate_num_9	-2.00675	.7580915	-2.65	0.008	-3.492583	-.5209183
_Istate_num_10	-2.829941	1.179243	-2.40	0.016	-5.141215	-.5186669
_Istate_num_11	-1.516505	.5505926	-2.75	0.006	-2.595646	-.4373631
_Istate_num_12	-.2144288	.0842717	-2.54	0.011	-.3795983	-.0492594
_Iyear_2018	-.1928766	1.396511	-0.14	0.890	-2.929988	2.544235
_cons	19.73654	6.308977	3.13	0.002	7.371169	32.10191

```
Endogenous: postlogcons
Exogenous:  log_gdpgrowth log_jobsprop _Istate_num_2 _Istate_num_3
            _Istate_num_4 _Istate_num_5 _Istate_num_6 _Istate_num_7
            _Istate_num_8 _Istate_num_9 _Istate_num_10 _Istate_num_11
            _Istate_num_12 _Iyear_2018 postlogchinaim
```

Second-stage regression (excluding time fixed effects) Stata-generated regression table:

```
i.state_num       _Istate_num_1-12    (naturally coded; _Istate_num_1 omitted)

Instrumental variables 2SLS regression          Number of obs   =         24
                                                Wald chi2(14)   =      10.84
                                                Prob > chi2     =     0.6984
                                                R-squared       =     0.8659
                                                Root MSE        =     .07581

                              (Std. err. adjusted for 12 clusters in state_num)
```

log_fav	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
log_total_cons	-2.219143	.8324309	-2.67	0.008	-3.850678	-.5876087
log_gdpgrowth	.0592251	.0515051	1.15	0.250	-.041723	.1601732
log_jobsprop	4.260565	1.368787	3.11	0.002	1.577792	6.943338
_Istate_num_2	-2.267417	.8846091	-2.56	0.010	-4.001219	-.5336155
_Istate_num_3	-1.233907	.4272377	-2.89	0.004	-2.071277	-.3965363
_Istate_num_4	3.138612	1.181898	2.66	0.008	.8221345	5.455089
_Istate_num_5	-.9298201	.3351202	-2.77	0.006	-1.586644	-.2729965
_Istate_num_6	-.1661902	.0739105	-2.25	0.025	-.3110521	-.0213283
_Istate_num_7	1.23056	.5605829	2.20	0.028	.1318371	2.329282
_Istate_num_8	2.650979	1.168528	2.27	0.023	.3607057	4.941252
_Istate_num_9	-1.353163	.4059211	-3.33	0.001	-2.148754	-.5575726
_Istate_num_10	-1.363911	.5517812	-2.47	0.013	-2.445383	-.2824402
_Istate_num_11	-.9257975	.2703725	-3.42	0.001	-1.455718	-.3958771
_Istate_num_12	-.4741133	.1073736	-4.42	0.000	-.6845618	-.2636649
_cons	51.73757	16.43647	3.15	0.002	19.52269	83.95245

```
Endogenous:  log_total_cons
Exogenous:   log_gdpgrowth log_jobsprop _Istate_num_2 _Istate_num_3
             _Istate_num_4 _Istate_num_5 _Istate_num_6 _Istate_num_7
             _Istate_num_8 _Istate_num_9 _Istate_num_10 _Istate_num_11
             _Istate_num_12 log_chinaimports
```

Appendix 4.

4.1

Stata code to generate graph

```
twoway lfit log_fav year
```

4.2

```
import matplotlib.pyplot as plt
import numpy as np

# Number of firms (n)
n = np.linspace(1, 20, 100)

# Plotting the PP Curve
# Let c = 2, b = 0.1
Average_P = 1 / (n * 0.1) + 2

# Plotting the CC Curve
# Let c = 2, F = 10, S = 20
Average_C = 2 + (10 * n) / 20

# Plotting the CC Curve with an added tariff
# Let t = 0.25
CC_and_t = 2 + (10 * n) / 20 + 0.5

# Create the plot
plt.figure(figsize=(10, 6))

# Plot the PP curve
plt.plot(n, Average_P, label='PP Curve')

# Plot the CC curve
plt.plot(n, Average_C, label='CC Curve')

# Plot the new steeper CC curve
plt.plot(n, CC_and_t, label='CC Curve with Tariff')

# Add labels and title
plt.xlabel('Number of Firms')
plt.ylabel('Average Price / Cost')
plt.title('PP and CC Curves under the New Trade Model')
plt.legend()
plt.grid(True)

# Hide y and x axis numbers
plt.xticks([])
plt.yticks([])

# Display the plot
plt.show()
```

Appendix 5.

Appendix 6.

For further research, we recommend studies on the effects of the US-China Trade war on other countries and the international shift of power. The US and China are both in the process of decoupling from each other; this has resulted in developing countries such as Vietnam receiving large inflows of foreign investment and trade from the US with China. The trade war has also sped up China's agenda of expanding its influence through the Belt and Road Initiative. International organizations have lost significant amounts of power due to the war; for example, the 'Most Favored Nation' has been violated many times by both countries, with little punishment for either country exercising their economic power[5]. This reduces the WTO's power of precedent, and potentially undoes decades of trade talks in reducing trade barriers.

Economic power – in the context of our analysis, the capacity of a country to affect another country's economic outcomes. For example, the ability of China to change macroeconomic outcomes of the USA using tariffs.

References

American Economic Association. (2019). Data and Code for: The economics of poverty traps. Journal of Economic Perspectives, 33(4), 187. DOI: 10.1257/jep.33.4.187. Dataset retrieved June 5, 2024, from https://www.aeaweb.org/journals/dataset?id=10.1257/jep.33.4.187

Amiti, M., Redding, S. J., & Weinstein, D. E. (2019). The impact of the 2018 tariffs on prices and welfare. Journal of Economic Perspectives, 33(4), 187-210.

Amnesty International. (2020, October 6). A licence to discriminate: Trump's Muslim & refugee ban. Www.amnesty.org.uk. https://www.amnesty.org.uk/licence-discriminate-trumps-muslim-refugee-ban

Autor, D., Dorn, D., Hanson, G., & Majlesi, K. (2017). A note on the effect of rising trade exposure on the 2016 presidential election. Appendix to "Importing Political Polarization, 3139-83

[5] Economic power – in the context of our analysis, the capacity of a country to affect another country's economic outcomes. For example, the ability of China to change the macroeconomic outcomes of the USA using tariffs.

Bachmann R and Braun S (2011) The impact of international outsourcing on labour market dynamics in Germany. Scottish Journal of Political Economy 58(1), 1–28.

Baldwin, R., 2011. Trade and Industrialization after Globalization’s 2nd Unbundling: How Building and Joining a Supply Chain Are Different and why it Matters. vol.

Blanchard, E. J., Bown, C. P., & Chor, D. (2024). Did Trump’s trade war impact the 2018 election? Journal of International Economics, 148, 103891. https://doi.org/10.1016/j.jinteco.2024.103891

Bown, C. P. (2023, April 6). US-China Trade War Tariffs: An Up-to-Date Chart.

Bureau of Economic Analysis. (2024). Table 101: Major Area, State, Levels, and Year 2016. Retrieved June 5, 2024, from https://apps.bea.gov/itable/?ReqID=70&step=1&_gl=1ge3z9m_gaMTEyMzEzMzI5My4xNzE3NDkwNzk0_ga_J4698JNNFT*MTcxNzUwNzQzMC4yLjEuMTcxNzUwODcwMS42MC4wLjA.#eyJhcHBpZCI6NzAsInN0ZXBzIjpbMSwyOSwyNSwzMSwyNiwyNywzMF0sImRhdGEiOltbIlRhYmxlSWQiLCIxMDEiXSxbIk1ham9yX0FyZWEiLCIwIl0sWyJTdGF0ZSIsWyIwIl1dLFsiQXJlYSIsWyJYWCJdXSxbIlN0YXRpc3RpYyIsWyIxIl1dLFsiVW5pdF9vZl9tZWFzdXJlIiwiTGV2ZWxzIl0sWyJZZWFyIixbIjIwMTYiXV0sWyJZZWFyQmVnaW4iLCItMSJdLFsiWWVhcl9FbmQiLCItMSJdXX0=

Bureau of Economic Analysis. (2024). Table 531: Major Area, State, and Percent Change. Retrieved June 5, 2024, from https://apps.bea.gov/itable/?ReqID=70&step=1&acrdn=1#eyJhcHBpZCI6NzAsInN0ZXBzIjpbMSwyOSwyNSwzMSwyNiwyNywzMF0sImRhdGEiOltbIlRhYmxlSWQiLCI1MzEiXSxbIk1ham9yX0FyZWEiLCIwIl0sWyJTdGF0ZSIsWyIwIl1dLFsiQXJlYSIsWyJYWCJdXSxbIlN0YXRpc3RpYyIsWyIxIl1dLFsiVW5pdF9vZl9tZWFzdXJlIiwiUGVyY2VudENoYW5nZSJdLFsiWWVhciIsWyItMSJdXSxbIllllYXJCZWdpbiIsIi0xIl0sWyJZZWFyX0VuZCIsIi0xIl1dfQ==

Cang, A., & Zhou, J. (2024, June 13). Chinese trader’s $20 million pile of Russian copper goes missing. Bloomberg. Retrieved June 13, 2024, from https://www.bloomberg.com/news/articles/2024-06-13/chinese-trader-caught-in-20-million-russian-copper-puzzle

China | Trade Summary | 2016 | WITS | Data. (2016). Worldbank.org. https://wits.worldbank.org/CountryProfile/en/Country/CHN/Year/2016/Summary

Chyzh, O. V., & Urbatsch, R. (2021). Bean Counters: The Effect of Soy Tariffs on Change in Republican Vote Share between the 2016 and 2018 Elections. The Journal of Politics, 83(1), 415–419. https://doi.org/10.1086/709434

Ebenstein, A., Harrison, A., McMillan, M., & Phillips, S. (2014). Estimating the Impact of Trade and Offshoring on American Workers using the Current Population Surveys. *The Review of Economics and Statistics*, 96(4), 581–595. https://doi.org/10.1162/rest_a_00400

Economic Research Service. (2024, February 7). Government payments by program. U.S. Department of Agriculture. Retrieved June 13, 2024, from https://data.ers.usda.gov/reports.aspx?ID=17833

Economic Research Service. (2024, April 19). Ag and food sectors and the economy. U.S. Department of Agriculture. Retrieved June 13, 2024, from https://www.ers.usda.gov/data-products/ag-and-food-statistics-charting-the-essentials/ag-and-food-sectors-and-the-economy/

Election 2016: results by state. (2017, February). Statista. https://www.statista.com/statistics/630799/preliminary-results-of-the-2016-presidential-election/Fajgelbaum, F.D., Goldberg, P.K., Kennedy, P.J., Khandelwal, A.K., 2020. The return to protectionism. Q. J. Econ. 135 (1), 1–55.

Fajgelbaum, F.D., Goldberg, P.K., Kennedy, P.J., Khandelwal, A.K., 2020. The return to protectionism. Q. J. Econ. 135 (1), 1–55.

Fetzer, T., & Schwarz, C. (2020). Tariffs and Politics: Evidence from Trump's Trade Wars. The Economic Journal, 131(636), 1717–1741. https://doi.org/10.1093/ej/ueaa122

Flaaen, A., Pierce, J.R., 2019. Disentangling the Effects of the 2018–2019 Tariffs on a Globally Connected US Manufacturing Sector (Federal Reserve Board Working Paper).

Görg H and Hanley A (2005) Labour demand effects of international outsourcing: evidence from plant-level data. International Review of Economics & Finance 14(3), 365–376.

Grossman, G.M., Rossi-Hansberg, E., 2006. The Rise of Offshoring: It's Not Wine for Cloth Anymore. The New Economic Geography: Effects and Policy Implications. w17716. National Bureau of Economic Research.

Huang, Y., Lin, C., Liu, S., & Tang, H. (2023). Trade networks and firm value: Evidence from the U.S.-China trade war. Journal of International Economics, 145, 103811-. https://doi.org/10.1016/j.jinteco.2023.103811

International Trade Administration. (n.d.). Foreign retaliations timeline. U.S. Department of Commerce. Retrieved June 13, 2024, from https://www.trade.gov/feature-article/foreign-retaliations-timeline

International Trade Administration. (n.d.). TradeStats Express: Year-to-date trade by partner and state. Retrieved June 5, 2024, from https://www.trade.gov/data-visualization/tradestats-express-year-date-ytd-trade-partner-state

Ipsos. (2024, June 1). Topline ABC/Ipsos poll. Ipsos. Retrieved June 13, 2024, from https://www.ipsos.com/sites/default/files/ct/news/documents/2024-06/Topline%20ABC_Ipsos%20Poll%20June%201%202024.pdf

Jackson, C., Newall, M., & Sawyer, J. (2024, June 2). Trump guilty verdict makes minimal impact on public opinion. https://www.ipsos.com/en-us/trump-guilty-verdict-makes-minimal-impact-public-opinion

Johnson, R.C., Noguera, G., 2012. Accounting for intermediates: production sharing and trade in value added. J. Int. Econ. 86 (2), 224–236.

Kim, S. E., & Margalit, Y. (2021). Tariffs As Electoral Weapons: The Political Geography of the US–China Trade War. International Organization, 75(1), 1–38. doi:10.1017/S0020818320000612

Li, B., Lu, Y., Sgro, P. M., & Xu, X. (2022). Trump, China, and the Republicans. Social Science Research Network. https://doi.org/10.2139/ssrn.4120755

Liu, T., & Woo, W. T. (2018). Understanding the U.S.-China Trade War. *China Economic Journal*, *11*(3), 319–340. https://doi.org/10.1080/17538963.2018.1516256

McCammon, S. (2016, November 5). Donald Trump Has Brought On Countless Controversies In An Unlikely Campaign. NPR.org. https://www.npr.org/2016/11/05/500782887/donald-trumps-road-to-election-day

National Agricultural Statistics Service. (2019, April 19). Cold storage. U.S. Department of Agriculture. Retrieved June 13, 2024, from https://www.nass.usda.gov/Publications/Todays_Reports/reports/fnlo0419.pdf

Needham, V. (2016, July 24). *Trump suggests leaving WTO over Import tax proposal*. The Hill. https://thehill.com/policy/finance/289005-trump-suggests-leaving-wto-over-import-tax-proposal/

Pappas, S. (2020, October 1). The toll of job loss. Monitor on Psychology. American Psychological Association. Retrieved June 13, 2024, from https://www.apa.org/monitor/2020/10/toll-job-loss

Rickard, S. J. (2022). Incumbents Beware: The Impact of Offshoring on Elections. British Journal of Political Science, 52(2), 758–780. doi:10.1017/S0007123420000757

Stanage, N. (2017, December 24). The Memo: The Top 10 Trump controversies of 2017. https://thehill.com/homenews/campaign/366336-the-memo-the-top-10-trump-controversies-of-2017/

State and Local General Expenditures, Per Capita. (2020, March 10). Tax Policy Center. https://www.taxpolicycenter.org/statistics/state-and-local-general-expenditures-capita

Statista. (2024). Chained inflation rate in the U.S. since 2001. Retrieved June 5, 2024, from https://www.statista.com/statistics/191119/chained-inflation-rate-in-the-us-since-2001/

Statista. (2024). Preliminary results of the 2016 Presidential Election. Retrieved June 5, 2024, from https://www.statista.com/statistics/630799/preliminary-results-of-the-2016-presidential-election/

Tax Policy Center. (2023). State and local general expenditures per capita. Retrieved June 5, 2024, from https://www.taxpolicycenter.org/statistics/state-and-local-general-expenditures-capita

The Library of Economics and Liberty. (n.d.). Paul Krugman. Retrieved June 13, 2024, from https://www.econlib.org/library/Enc/bios/Krugman.html

Trump puts burden of scrapping Iran deal on US Congress. (n.d.). Al Jazeera. Retrieved June 5, 2024, from https://www.aljazeera.com/news/2017/10/13/iran-nuclear-deal-donald-trump-decertifies-2015-pact/

Vogel, K. P. (2017, January 31). Trump raised $11 million in December.

Waugh, M. (2019). The Consumption Response to Trade Shocks: Evidence from the Us-China Trade War. Social Science Research Network. https://doi.org/10.2139/ssrn.3465371

Yang, S., & Shumway, C. R. (2020). Knowledge accumulation in US agriculture: research and learning by doing. Journal of Productivity Analysis, 54(2–3), 87–105. https://doi.org/10.1007/s11123-020-00586-6

Zeng, K. (2023, February 17). Gauging the impact of the China-US trade war. The Diplomat. Retrieved June 13, 2024, from https://thediplomat.com/2023/02/gauging-the-impact-of-the-china-us-trade-war/

Zheng, J., Zhou, S., Li, X., Padula, A. D., & Martin, W. (2023). Effects of Eliminating the US–China Trade Dispute Tariffs. World Trade Review, 22(2), 212–231. doi:10.1017/S1474745622000271