Politically Motivated Trade Protection*

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January 2024
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Abstract

The Electoral College system used to elect US presidents has been widely criticized and many proposals have been put forward to reform it. This paper shows that this electoral system distorts US federal policies in favor of key industries in swing states, at the expense of other industries. Using detailed data on US trade policies during the last decades, we find that the level of trade protection granted to an industry during a presidential term depends on its importance in states expected to be swing in that term. Crucially, swing-state politics only matters during first terms, when the incumbent president can be re-elected. We next examine the effects of politically motivated trade protection, exploiting exogenous changes in the identity of swing states across terms and heterogeneous exposure to these political shocks across industries. We find that swing-state politics generates winners and losers: it fosters growth in protected industries, but hampers growth in downstream industries.

JEL Classifications: D72, D78, F13.

Keywords: Electoral College, Swing States, Trade Protection, Supply Chains.

*This paper builds on two earlier projects circulated under the titles "Trade Protection Along Supply Chains" and "Trade Policy and the China Syndrome." We wish to thank for their comments and suggestions Pol Antràs, Tommaso Aquilante, Andy Bernard, Emily Blanchard, Kirill Borusyak, Renee Bowen, Davin Chor, Italo Colantone, Ruben Durante, Brian Kovak, Marcelo Olarreaga, Emanuel Ornelas, Justin Pierce, Vincent Pons, Giacomo Ponzetto, Vincent Rebeyrol, Peter Schott, Jesse Shapiro, Jan Schymik, Marco Tabellini, Hylke Vandenbussche, Noam Yuchtman, Chris Woodruff, Maurizio Zanardi, participants at the NBER Political Economy Meeting Fall 2023, the ETSG and CEBLF conferences, the FREIT SETC conference, the CESifo conference on the Global Economy, the Fifth Conference of CEPR Research Network on Global Value Chains, Trade and Development, the Workshop on International Economic Networks, the Spring Meeting of Young Economists, the Geneva Trade and Development Workshop, the Workshop on International Trade: The New Normal, the Trade Policy and GVCs Workshop at Mannheim University, the 2022 AEA conference, the 2021 CEPR ERWIT conference, the EOS conference, the IEA World Congress, and seminar participants at London School of Economics, Columbia University, UZH, UBC, Warwick, Oxford, Trinity College Dublin, ECARES, Lancaster University, Erasmus University Rotterdam, Maastricht University, Syracuse University, Nottingham University, University of Mainz, University of Munich, the Empirical Trade Online Seminar, and the Bank of Italy. We are grateful to Elisa Navarra for excellent research assistance. Paola Conconi acknowledges funding from the FNRS, the European Research Council (Advanced ERC Grant No. 834253) and the European Union's Horizon 2020 research and innovation programme (Agreement Grant No. 770680), while Lorenzo Trimarchi acknowledges funding from the FNRS (Excellence of Science Research No. O020918F). Correspondence should be addressed to Paola Conconi, paola.conconi@economics.ox.ac.uk.

1 Introduction

The president of the United States, one of the world's most powerful political leaders, is not directly elected by popular vote. Citizens express their preference for a candidate from one party. The party that wins a majority of votes in a state appoints *all* the "electors" of that state. The electors from the different states form the Electoral College, which chooses the president.[1]

This electoral system has been widely criticized and many proposals have been put forward to reform it or even abolish it, to no avail so far.[2] One of the main criticisms is that the system delivers undemocratic outcomes, since it does not align with the "one person, one vote" principle: only citizens who vote in line with the majority in their state have a voice in the Electoral College. As a result, in several elections, the outcome has gone against the popular vote (e.g., in 2016, when Hillary Clinton won the popular vote but Donald Trump won in the Electoral College). Another major criticism is that the winner-takes-all nature of this electoral system creates incentives for politicians to target "swing" states, in which a small difference in votes can shift all electors from one candidate to the other. There is evidence that swing-state politics affects presidential candidates' campaign visits (Strömberg, 2008), but much less is known about the effects on actual policy choices.

In this paper, we show that the Electoral College system distorts federal policies, giving rise to distributional effects: to get re-elected, incumbent executives implement policies that are beneficial to key industries in swing states, but are detrimental to other industries. We focus on trade policy, which is exclusively set at the federal level and can be easily adjusted to protect key industries in battleground states. The argument that swing-state politics affects US protectionist measures is often heard in the media. For example, during his first term, President George W. Bush introduced several measures on imports of steel from China and other countries, to gain votes in various states in the Rust Belt, which were expected to be swing in the next presidential elections.[3] We provide systematic evidence that swing-state politics shapes US protectionist measures. Our main focus is antidumping (AD) duties, the primary form of trade protection worldwide (Pierce, 2011; Blonigen and Prusa, 2016).[4]

[1] Of the current 538 electors, a majority of 270 or more electoral votes is required to elect the president.

[2] To ensure that the candidate who receives the most votes nationwide is elected president, sixteen states have adopted the National Popular Vote Interstate Compact, an agreement to award all their electoral votes to whichever presidential ticket wins the overall popular vote in the 50 states and the District of Columbia.

[3] See "Bush policies follow politics of states needed in 2004" (*USA Today*, June 16, 2002). During the same term, President Bush introduced several other protectionist measures, including some against imports of furniture from China, which were seen as motivated by re-election motives (see "China's Furniture Boom Festers in U.S.," *The New York Times*, January 29, 2004).

[4] Our results are robust to including other temporary trade barriers (TTBs), such as countervailing duties

While these measures are designed to defend producers against "unfair" import competition, they are considered to be "simply a modern form of protection" (Blonigen and Prusa, 2003).

It has long been known that AD duties are often manipulated for political purposes (e.g., Finger *et al.*, 1982), since they can be easily adjusted to shelter some industries from import competition from particular countries. By contrast, most-favored-nation (MFN) tariffs are less flexible, since they are bound to the levels agreed upon during multilateral negotiations and cannot be targeted to particular countries (Alfaro *et al.*, 2016). The AD process in the United States starts with a petition from representatives of an industry claiming injury caused by unfairly priced products imported from a specific country. Two key institutions decide on the outcome of the petition (see Section 3 for more details): the Department of Commerce (DOC), which determines whether the products have been sold at "less than fair value" and sets the dumping margin; and the International Trade Commission (ITC), which determines whether the dumped imports have caused material injury to the US industry. Political considerations can directly affect the decisions of the DOC, which is part of the executive branch.[5] The executive can thus directly intervene in these decisions.[6] There is also evidence that ITC commissioners are subject to political pressure (e.g., Hansen and Prusa, 1997; Aquilante, 2018).

We focus on US AD duties against China. There are two main reasons for this choice. First, the last decades have witnessed the rise of China as a world trading power, with sizable effects on US labor market outcomes (Autor *et al.*, 2013). As a result, US voters see trade with China as a major threat. As documented by Alfaro *et al.* (2023), "concerns over the role of China as a major U.S. trading partner and the associated concerns about jobs loom large as priors in the minds of the American public when the issue of trade is raised." Consequently, China is by far the biggest target of US AD protection: 73% of US AD measures have targeted China since its accession to the WTO. Second, duties against China can more easily be manipulated for political purposes due to its non-market economy (NME) status.[7] AD petitions involving China thus result in much higher duties: between

and safeguards, which are much less frequently used than AD duties (see Figure A-1).

[5]The White House can shape DOC decisions through various political appointments. For example, the President nominates the top positions (Secretary, Deputy Secretary), as well as the key positions in charge of AD (e.g., Under Secretary for International Trade, Assistant Secretary for Market Access and Compliance).

[6]For example, in 2017 the DOC reversed its prior negative position on an AD case after Peter Navarro, Director of the National Trade Council under Trump, sent a "Recommendation for Action" letter (see US Court of International Trade, Consol. Court No. 17-00091).

[7]Article 15 of China's Protocol of Accession to the WTO allowed other members to treat China as a NME until December 2016. To this day, the United States has refused to grant China the market economy status. This implies that DOC officials can use flexible methods in their AD decisions, using price and cost information from surrogate countries.

1989 and 2020, the average US AD duty against China was 160%, compared to 48% for other target countries. The fact that political motives drive AD duties against China is reflected in the lack of correlation between the extent of protection granted to a sector and its exposure to import competition.[8]

Our main analysis spans the eight presidential terms covering the period 1989-2020.[9] In line with previous studies, states are classified as swing if the vote margin between Democratic and Republican candidates falls below a critical threshold. In our baseline analysis, we use data on midterm congressional elections to obtain arguably exogenous variation in the states expected to be swing during a presidential term.[10] The results are robust to defining swing states using data on presidential elections.

We show that the level of AD protection granted to an industry during a term depends on its importance (in terms of employment) in states expected to be swing in that term. However, this is only true during executive first terms, when the incumbent president can be re-elected; swing-state politics does not affect AD duties during second terms, when the president is a lame duck. In line with the theoretical model of Conconi *et al.* (2017), these results suggest that the Electoral College leads US presidents facing re-election to manipulate trade policy in favor of key industries in swing states.

The effect of swing-state politics is sizeable: a one standard deviation increase in the importance of an industry in states classified as swing during first terms increases the level of protection by around 0.4 percentage points, explaining 18% of the average level of protection in our sample. The results continue to hold in a battery of robustness checks, including using different methodologies to address possible identification concerns.

We further provide micro-level evidence that swing-state politics affects actual AD decisions. To this purpose, we collect all votes on AD cases by ITC commissioners during the last few decades. We show that, during executive first terms, individual ITC commissioners are more likely to vote in favor of the petitioning industry when this is more important in states expected to be swing. In terms of magnitude, a one standard deviation increase in the importance of an industry in states expected to be swing increases the probability of a positive vote by 12 percentage points.

[8]The correlation between our baseline measure of AD protection and the import penetration ratio from China is close to zero (-0.017) and insignificant.

[9]In robustness checks, we show that our results continue to hold if we exclude the presidency of Donald Trump, who led to an unprecedented rise in trade protection via special tariffs (in addition to AD duties). These were introduced under Section 232 of the Trade Expansion Act of 1962 and Sections 201 and 301 of the Trade Act of 1974 (Bown, 2019) and have triggered the ongoing trade war with China.

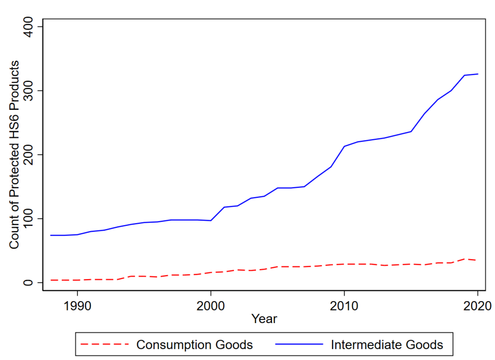
[10]We focus on House elections, which take place in all states every two years. This is not the case for Senate and gubernatorial elections, which are not carried out throughout the entire country.

To study the effects of politically motivated protection, we propose a novel shift-share instrument for AD duties. In our setting, the shifters are changes in the identity of states expected to be swing in the next presidential elections, which generate plausibly exogenous political shocks.[11] Exposure to political shocks varies across industries, depending on their importance across states (captured by pre-sample employment levels) and vertical linkages between them (captured by input-output coefficients at the start of the sample period). We also exploit variation across industries in their historical experience in the AD process (captured by the count of pre-sample petitions). This makes the instrument specific to AD duties, alleviating concerns about the exclusion restriction. The logic behind the instrument is that AD protection should be skewed in favor of important industries in swing states, but only if they have prior knowledge of the complex procedures to petition for AD duties.[12]

We use the instrument to identify the effects of politically motivated trade protection on directly and indirectly exposed industries. In a world in which production processes are fragmented across countries (Antràs and Chor, 2022), the effects of trade barriers can propagate along supply chains. Concerns about the negative effects of trade protection on downstream industries are particularly severe for AD duties: unlike MFN tariffs, these measures are skewed towards key input industries (e.g., steel, chemicals, plastics and rubber, industrial machinery, auto parts).

Figure 1

US AD Duties on Intermediate and Consumption Goods



The figure shows the count of HS6 products involving US AD duties against China during 1989-2020. We use the UN BEC classification to distinguish between intermediate and consumption goods.

[11]In line with the assumption of exogenous political shocks, we show that the identity of swing states is uncorrelated with state-level characteristics (the extent to which industries in the state have been exposed to trade protection and import competition, and the degree to which employment has been declining).

[12]As pointed out by Blonigen and Park (2004) and Blonigen (2006), the legal and institutional complexity of this process implies that industries with prior experience in AD cases face lower costs of filing and a higher probability of success in new cases.

The fact that AD protection is biased towards intermediate inputs can be seen in Figure 1, which illustrates the evolution of AD duties on intermediate and consumption goods during our sample period. By 2020, 326 HS6 products coded as intermediate goods in the Broad Economic Categories (BEC) classification had AD duties against China, corresponding to 10.5% of products in this category.

We find that politically motivated trade protection generates winners and losers along supply chains. On the one hand, it fosters employment growth in protected industries. Our baseline two-stage least squares (2SLS) estimates imply that a one standard deviation increase in AD protection increases the growth rate of employment in protected industries by 5.9 percentage points. On the other hand, AD duties reduce employment growth in downstream industries, which rely on protected inputs. Our baseline estimates imply that a one standard deviation increase in input protection decreases the employment growth rate by 2.3 percentage points. We also provide evidence of the negative effects of AD protection on targeted imports: a one standard deviation increase in trade protection decreases imports from China by 43 percentage points, with no significant effects on imports from the rest of the world.

Our identification strategy relies on exogenous political shocks driven by changes in the identity of swing states across electoral terms. As pointed out by Borusyak and Hull (2023), even if the shocks are randomly assigned, 2SLS estimates may suffer from an omitted variable bias if exposure to the shocks is not random. To address this concern, we show that our results are unaffected if we apply their "recentering" procedure by considering counterfactual shocks. They also continue to hold in a series of additional robustness checks, e.g., when we use different measures of AD protection, include in our analysis other temporary trade barriers (countervailing duties and safeguards), or consider different sample periods.

Our analysis provides new arguments for the need to reform the Electoral College. It shows that this electoral system leads to distorted economic policies, aimed at protecting industries that are important in states expected to be swing during an electoral term. These policies generate winners and losers across industries, in line with arguments often heard in the media.[13] Our results imply that, if US voters directly elected the president, industries producing key intermediate inputs, such as metals, industrial machines, and transportation equipment, would receive lower trade protection, benefiting other sectors in the economy.

[13]For example, the CEO of the Bicycle Corporation of America complained about tariffs on Chinese imports of bike components, steel and aluminum, which have raised production costs. As a result, the industry's "plans to expand are on hold, costing American jobs." See "The Trouble with Putting Tariffs on Chinese Goods" (*The Economist*, May 16, 2019).

The rest of the paper is structured as follows. In Section 2, we briefly review the related literature. Section 3 provides information on the institutional procedures for the introduction of AD duties in the United States. Section 4 describes the data and variables used in our empirical analysis. Section 5 examines the impact of swing-state politics on US trade protection. Section 6 presents the 2SLS results on the effects of politically motivated trade protection on industries directly and indirectly exposed to it. Section 7 concludes.

2 Related Literature

Our paper builds on several streams of literature. The influential literature on political business cycles reviewed by Drazen (2000) emphasizes the importance of electoral calendars when politicians are office motivated. Close to elections, incumbent politicians manipulate fiscal and monetary policies to signal their competence (e.g., Rogoff and Sibert 1988; Rogoff, 1990; Alesina and Roubini, 1992). In particular, electoral rules can affect rent extraction and policy outcomes (e.g., Persson *et al.*, 1997; Persson *et al.*, 2003; Persson and Tabellini, 2004; Ferraz and Finan, 2011). Only some studies consider the system used to elect US presidents. Strömberg (2008) shows that US presidential candidates allocate their campaign resources toward swing states to maximize the probability of winning the election. Some studies document a swing-state bias in US trade policy. Muûls and Petropoulou (2013) show that states classified as swing in President Reagan's first term benefited from higher protection. Conconi *et al.* (2017) find that US presidents are more likely to initiate trade disputes that involve key industries in swing states, particularly when they face re-election. Ma and McLaren (2018) study the effects of local partisanship in a model of electoral competition and show that swing-state politics shaped US MFN tariffs at the end of the Uruguay Round in 1994. Ours is the first paper to show that the Electoral College creates incentives to protect key input industries, with significant distributional effects along supply chains.

Our analysis is also related to the large literature on AD duties reviewed by Blonigen and Prusa (2016). Some studies examine their determinants (e.g., Finger *et al.*, 1982; Bown and Crowley, 2013). Others examine their effects on imports from targeted countries,[14] or the indirect effects on third countries (e.g., Prusa, 1997; Bown and Crowley, 2007; Vandenbussche and Zanardi, 2010). A few studies examine the effects on welfare (Gallaway *et al.*, 1999)

[14]For example, Prusa (2001) provides evidence for the trade destruction effect of AD protection, showing that US AD measures decreased imports of targeted products by between 30% and 50%. On the extensive margin, Besedes and Prusa (2017) find that US AD increases the probability of foreign firms exiting the US market by more than 50%. Lu *et al.* (2013) use detailed transaction data on Chinese firms and find that an increase in US AD duties leads to a significant drop in Chinese exports to the United States.

and FDI (Blonigen, 2002). To deal with the endogeneity of AD protection, some authors combine a difference-in-differences methodology with propensity score matching (Konings and Vandenbussche, 2008; Pierce, 2011). As mentioned before, various studies emphasize political economy drivers of US AD duties (e.g., Finger *et al.*, 1982; Moore, 1992; Hansen and Prusa, 1997; Aquilante, 2018). Ours is the first paper to propose an instrumental variable for these measures and show that they are shaped by swing-state politics.

Finally, our paper contributes to the literature on trade policy and input-output linkages. Our findings are in line with previous theoretical and empirical studies on the effects of trade protection along supply chains. Blonigen (2016) shows that AD duties applied to steel imports are harmful to downstream sectors. Barattieri and Cacciatore (2023) estimate the dynamic employment effects of AD duties. They find that these measures have small beneficial effects in protected industries, but negative effects on downstream industries. Various studies emphasize the productivity-enhancing effects of global sourcing and input trade liberalization (e.g., Amiti and Konings, 2007; Goldberg *et al.*, 2010; Halpern *et al.*, 2015; Antràs *et al.*, 2017; Blaum *et al.*, 2018). Others examine the negative effects of trade protection along value chains (e.g., Yi, 2003; Erbahar and Zi, 2017; Conconi *et al.*, 2018; Vandenbussche and Viegelahn, 2018; Jabbour *et al.*, 2019; Bown *et al.*, 2021; Barattieri and Cacciatore, 2023). Ours is the first paper to study the effects of trade protection motivated by political shocks.

3 AD Protection in the United States

Antidumping duties are meant to protect domestic producers against unfair trade practices by foreign firms. Under Article VI of the General Agreement on Tariffs and Trade (GATT) and US trade laws, dumping occurs when goods are exported at a price "less than fair value" (LTFV), i.e., for less than they are sold in the domestic market or at less than production cost. Multilateral trade rules allow unilateral measures against dumped imports that cause material injury to domestic producers.

In the United States, AD is administrated by two agencies, each with different competencies: the US Department of Commerce (DOC),[15] which is in charge of the dumping investigation, and the US International Trade Commission (ITC), which is in charge of the injury investigation. The DOC is an integral part of the US Administration, while the

[15] Before 1980, the US Department of Treasury was in charge of dumping investigations. The US Congress moved this responsibility from the Treasury to the Department of Commerce, which was seen as more inclined to protect US firms and workers than the Treasury (Irwin, 2005).

ITC is a bipartisan agency composed of six commissioners nominated by the President and confirmed by the Senate (with no more than three commissioners from the same party).

An AD case starts with a petition filed to the ITC and the DOC, claiming injury caused by unfairly priced products imported from a specific country.[16] US manufacturers or wholesalers, trade unions, and trade or business associations are all entitled to be petitioners, to the extent that they represent their industries. The petitioning process is highly complex, requiring petitioners to provide extremely detailed information about the case.[17]

Once a petition has been filed, the DOC decides whether a product is "dumped," i.e., imported at LTFV. A product is declared to be dumped if the dumping margin is above a threshold established by the DOC. According to the law, the DOC defines fair value as the foreign firm's price of the same good in its home country. However, in the case of non-market economies like China, the DOC can rely on surrogate countries to determine the dumping margin. When focusing on cases targeting China during 1989-2020, the DOC ruled in favor of dumping in 99% of the cases.

In the administration of antidumping, the ITC is in charge of the injury investigation. Under the US Tariff Act of 1930, the ITC "determines whether an article is being imported into the United States in such increased quantities as to be a substantial cause of serious injury, or the threat thereof, to the domestic industry producing an article like or directly competitive with the imported article." If the ITC finds that the relevant US industry has been materially injured, or threatened with material injury, an AD duty equal to the dumping margin established by the DOC is introduced. During 1989-2020, the ITC ruled in favor of the petitioning industry in 77% of the cases targeting China. The average AD duty against China was 160%.

After positive rulings by both the DOC and the ITC, AD measures are introduced for

[16] An AD case may concern multiple petitions involving different countries exporting the same product. For instance, in 2008, the AD case regarding "Light-Walled Rectangular Pipe and Tube" (USITC investigations 731-TA-1118 – 731-TA-1121) targeted imports from China, Korea, Mexico, and Turkey.

[17] Petitioners must provide the identity of all producers in the industry and their position regarding the petition, as well as detailed descriptions and supporting documentation of the material injury to the industry due to the increased level of imports (e.g., lost sales, decreased capacity utilization, or company closures). Among others, they also need to provide: "detailed description of the imported merchandise, including technical characteristics and uses; the volume and value of each firm's exports of the merchandise to the United States during the most recent 12-month period; the home market price in the country of exportation; evidence that sales in the home market are being made at a price which does not reflect the cost of production and the circumstances under which such sales are made; the petitioner's capacity, production, domestic sales, export sales, and end-of-period inventories of U.S.-produced merchandise like or most similar to the allegedly dumped imports in the 3 most recent calendar years and in the most recent partial-year periods for which data are available" (see `https://enforcement.trade.gov/petitioncounseling/Guidelines-for-AD-Petitions-09-30-2015.pdf`).

a period of five years, after which they are subject to Sunset Reviews. Bown *et al.* (2021) document that US AD duties are usually extended and last on average for 12 years.

4 Data and Variables

4.1 Direct and Indirect Exposure to Trade Protection

Our source on protectionist measures is the Temporary Trade Barriers Database (TTBD) of Bown *et al.* (2020). The dataset contains detailed information on AD duties and other less commonly used forms of contingent protection (countervailing duties and safeguards) for more than thirty countries since 1980. For each case, it provides the identity of the country initiating it, the identity of the country subject to the investigation, the date of initiation of the investigation, the date of imposition of the measure (if the case is approved), as well as detailed information on the products under investigation. For the United States, products are identified at the 10-digit Harmonized Tariff Schedule (HTS) level (or at the 5-digit Tariff Schedule of the United States Annotated for years before 1989). Appendix A.1 details our matching procedure to link each investigation to a corresponding 4-digit Standard Industrial Classification (SIC4) code.

Our empirical analysis focuses on AD duties introduced by the United States against China. As mentioned in the introduction, protectionist measures against China should be more sensitive to electoral pressure, for two reasons: US voters perceive trade with China as a major threat, and US AD duties against China can be more easily manipulated for political purposes due to its NME status. Moreover, China is by far the most frequent target of US AD protection in our sample period. During the eight presidential terms covering 1989-2020, the US initiated 224 cases involving imports from China, accounting for almost half of the total caseload in this period.

To capture trade protection granted to SIC4 industry j during presidential term T, we define the variable $\textit{Trade Protection}_{j,T}$. In our baseline specification, this is the average share of HS6 products within industry j subject to AD duties during term T.[18] In robustness checks, we use two alternative measures: the average share of products within industry j subject to AD duties and other TTBs (countervailing duties or safeguards) during term T; and a dummy variable equal to 1 if HS6 products within industry j are subject to AD duties

[18]Recall that AD duties are subject to Sunset Reviews every five years. Within an industry j, variation in $\textit{Trade Protection}_{j,T}$ across electoral terms thus comes both from the imposition of new measures, and the revocation or renewal of old measures.

during term T.

To measure exposure to trade protection along supply chains, we use US input-output tables from the Bureau of Economic Analysis (BEA). We rely on the 1992 BEA benchmark input-output table, fixing technological linkages at the beginning of our sample period.[19] We convert 6-digit BEA industry codes into SIC4 codes to be able to combine input-output tables with industry-level data. This allows us to trace downstream and upstream linkages between 479 manufacturing and non-manufacturing industries. The disaggregated nature of the US input-output tables is one of the reasons why they have been used to capture technological linkages between sectors, even in cross-country studies (e.g., Alfaro *et al.*, 2016 and 2019).

Figure A-2 in the Appendix illustrates total cost and usage shares for the 479 SIC4 j industries, focusing on the top-50 input and output industries. Among input industries, some play a crucial role in the US economy. Notice that steel (SIC 3312) is the most important input for 82 industries (see Table A-1) and is also one of the primary recipients of AD protection (see Table A-3).

Combining information on US AD duties with the 1992 US input-output table, we can construct measures of direct and indirect exposure to trade protection along supply chains.[20] Direct exposure is captured by:

$$Direct\ Tariff\ Exposure_{j,T} = Trade\ Protection_{j,T}, \tag{1}$$

where $Trade\ Protection_{j,T}$ is the share of HS6 products within industry j that are subject to AD duties during term T (or one of the alternative protectionist measures). Exposure by downstream industries is given by:

$$Downstream\ Tariff\ Exposure_{j,T} = \sum_{i=1}^{N} \omega_{i,j}\, Trade\ Protection_{i,T}, \tag{2}$$

where $\omega_{i,j}$ is the cost share of input i in the production of j. This variable captures exposure to AD duties that protect j's suppliers. Similarly, we define exposure to trade protection by

[19]The data are available at `https://www.bea.gov/industry/benchmark-input-output-data`.

[20]Our measures of direct and indirect tariff exposure are in line with previous studies on the effects of trade policy changes (e.g., Topalova, 2010; Kovak, 2013).

upstream industries:

$$\textit{Upstream Tariff Exposure}_{j,T} = \sum_{i=1}^{N} \theta_{i,j} \textit{Trade Protection}_{i,T}, \tag{3}$$

where $\theta_{i,j}$ is the share of industry j's total sales that are used as inputs in the production of manufacturing industry i. This variable captures exposure to AD duties that protect j's customers.

We construct four versions of the downstream and upstream measures: the first two include the diagonal of the input output matrix ($\omega_{j,j}$ and $\theta_{j,j}$) and are either based on direct input-output linkages (version 1) or also account for higher-order linkages by using the Leontief inverse of the input-output matrix (version 2); the last two exclude the diagonal of the input-output matrix to isolate indirect effects, and either account for direct linkages only (version 3) or also for higher-order linkages (version 4). Table A-2 reports descriptive statistics of the tariff exposure variables.

4.2 Swing States

As mentioned in the introduction, the argument that US presidents manipulate trade policy in favor of key industries in swing states is often heard in the media. One of the main goals of our analysis is to verify whether swing-state politics systematically affects US protectionist measures. To this purpose, we need to identify which states are expected to be swing during a presidential term. One strategy would be to use data on the outcome of presidential elections and classify a state to be swing if the vote margin between the Democratic and Republican candidates falls below a critical threshold. A key concern with this strategy is that, if incumbent executives manipulate protectionist measures for electoral purposes, trade policy may affect the difference in votes between presidential candidates, and thus the identity of swing states.

To address this concern, in our baseline regressions, we use data on the outcome of midterm congressional elections to identify states expected to be swing in the next presidential elections.[21] Every two years, all 435 House seats are up for grabs.[22] We compute the difference in the share of votes received by the two parties in each state, excluding votes to

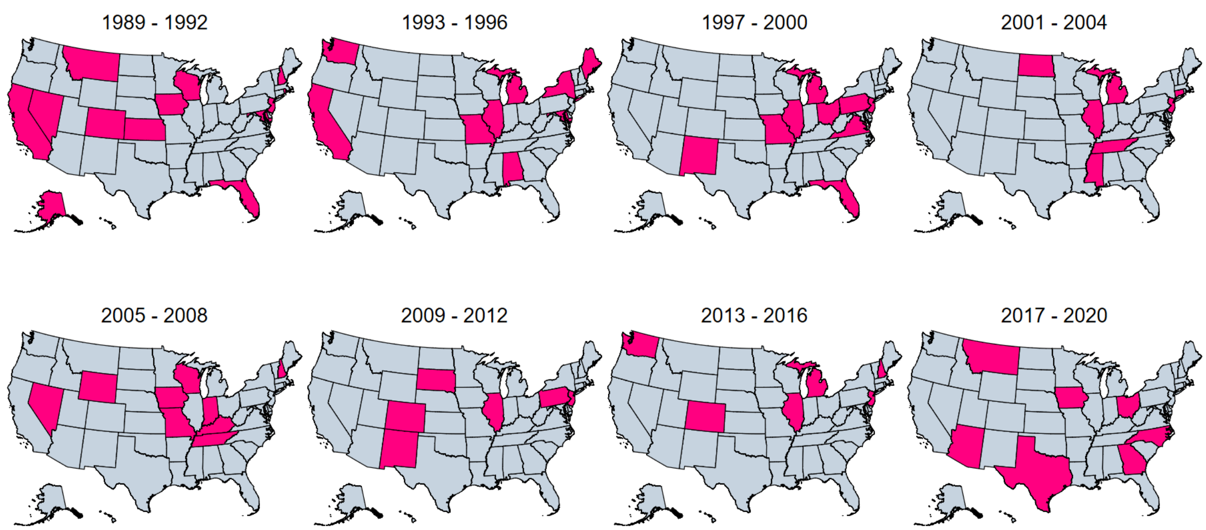
[21] The relevant midterm elections are thus 1990-2018. Data come from the MIT Election Data and Science Lab (see `https://electionlab.mit.edu`).

[22] This is not the case for Senate and gubernatorial elections, which are not carried out throughout the entire country. For this reason, we use the results in the House of Representatives to determine each party's presidential outlook.

candidates from third parties.[23] Battleground states are identified by the indicator variable $Swing\ State_{s,T}$, which is equal to 1 for state s during presidential term T if the vote margin between the Democratic and Republican candidates in the House elections in the middle of term T is below the 5% threshold, i.e., if candidates from the two parties obtain between 47.5% and 52.5% of the share of votes in the state. Figure 2 illustrates the states that are classified as swing during the 1989-2020 period using this definition. Notice that both the number and the identity of swing states vary across terms.

Figure 2

Swing States (Based on Midterm Elections)



The states in pink are those in which the difference in vote shares between Democratic and Republican House candidates in the House midterm elections is less than 5%: in 1989-1992, Alaska, California, Colorado, Florida, Iowa, Kansas, Maryland, Montana, New Jersey, Nevada, New Hampshire, Rhode Island, and Wisconsin; in 1993-1996, Alabama, California, Illinois, Maine, Maryland, Michigan, Missouri, New York, and Washington; in 1997-2000, Florida, Illinois, Michigan, Missouri, New Jersey, New Mexico, Ohio, Pennsylvania, and Virginia; in 2001-2004, Connecticut, Illinois, Michigan, Mississippi, New Jersey, North Dakota, and Tennessee; in 2005-2008, Kentucky, Indiana, Iowa, Missouri, New Hampshire, Nevada, Tennessee, Wisconsin, and Wyoming; in 2009-2012, Colorado, Illinois, New Jersey, New Mexico, Pennsylvania, and South Dakota; in 2013-2016, Colorado, Illinois, Michigan, New Hampshire, New Jersey, and Washington; in 2017-2020, Arizona, Georgia, Iowa, Montana, North Carolina, Ohio, and Texas.

In robustness checks, we use the outcome of presidential elections to identify battleground states. In particular, we classify a state s to be swing during presidential term T if the vote margin between the Democratic and Republican candidates in the presidential elections at the end of the term is below the 5% threshold.

[23] We use state-level rather than district-level outcomes because the presidency is won based on votes in states, not districts. Moreover, at the district level, House races are rarely competitive due to gerrymandering.

4.3 Importance of Industries in Swing States

To measure the importance of an industry j in states expected to be swing during electoral term T, we define the following variable:

$$\textit{Swing Industry}_{j,T} = \frac{\sum_s L_{s,j} \times \textit{Swing State}_{s,T} \times EV_s}{\sum_s \sum_j L_{s,j} \times \textit{Swing State}_{s,T} \times EV_s}. \tag{4}$$

To account for differences in the political importance of swing states, we multiply the dummy variable $\textit{Swing State}_{s,T}$ by EV_s, the number of electoral votes assigned to state s before the start of our sample period (in 1988).[24] The variable $L_{s,j}$ measures employment of industry j in state s and is also constructed using pre-sample (1988) data.[25] $\textit{Swing Industry}_{j,T}$ is thus the ratio of total employment in manufacturing industry j in states expected to be swing during term T, over total employment in those states.[26]

Within an industry j, variation in $\textit{Swing Industry}_{j,T}$ comes from changes in the identity of swing states across electoral terms (captured by the dummy variable $\textit{Swing State}_{s,T}$). Within a term T, cross-industry variation comes from differences in the importance of industries across states (captured by the pre-sample employment levels $L_{s,j}$). Descriptive statistics of the variable $\textit{Swing Industry}_{j,T}$ are reported in Table A-2. The top panel of Table A-3 lists the top-10 SIC4 sectors with the highest average value of $\textit{Swing Industry}_{j,T}$ during 1989-2020.

5 Swing-State Politics and US Trade Protection

In what follows, we provide systematic evidence that swing-state politics distorts US trade policy. In Section 5.1, we show that the level of AD protection granted to an industry during an electoral term depends on the importance of the industry in states expected to be swing during that term. The results are driven by executive first terms, when the incumbent president can be re-elected, and hold in a variety of alternative specifications (e.g., using various measures of trade protection, alternative definitions of swing states, and different sample periods). In Section 5.2, we show that results are also robust to using different

[24]The number of electoral votes allocated to a state is proportional to its population. The variable EV_s ranges between 3 (for Alaska, Delaware, District of Columbia, North Dakota, South Dakota, Vermont, and Wyoming) and 47 (for California).

[25]Using data from later years would yield very similar results, given that the geographical distribution of industries across states is very stable over time: the correlation between $L_{s,j}$ in 1988 (the last year before the start of our sample) and 2020 (the last year of our sample) is 0.9, as shown in Figure A-4.

[26]In our baseline regressions, the denominator of $\textit{Swing Industry}_{j,T}$ is constructed using information on state-level employment in all sectors. As discussed below, the results are robust to replacing the denominator of (4) with state-level employment in manufacturing sectors only.

strategies to address identification concerns. Finally, in Section 5.3 we provide micro-level evidence that swing-state politics shapes AD votes of ITC commissioners.

5.1 The Impact of Swing-State Politics on the Level of Protection

Our empirical analysis is guided by the theoretical model of Conconi *et al.* (2017), which has two key features. First, voters have reciprocal preferences, i.e., they want to reward politicians who have been kind to them and punish politicians who have been unkind to them.[27] Crucially, reciprocal preferences only matter if voters are not too ideological and can thus be "swung" by trade policy choices. Second, the incumbent's ability to set trade policy provides an advantage over the challenger, who cannot commit to trade policy before being elected. A key implication of this model is that re-election motives should lead the incumbent executive to manipulate trade policy in favor of key industries in swing states.[28] Moreover, if voters reward or punish the incumbent executive (rather than his party), swing-state politics should only affect trade protection during first terms, when the president can be re-elected.

To assess the validity of these predictions, we exploit variation in the political importance of industries driven by changes in the identity of swing states across electoral terms. We estimate the following regression separately for executive first terms (when the executive can be re-elected) and second terms (when the executive is a lame duck):

$$Trade\ Protection_{j,T} = \beta_0 + \beta_1 Swing\ Industry_{j,T} + \delta_j + \delta_T + \varepsilon_{j,T}, \tag{5}$$

where $Swing\ Industry_{j,T}$ captures the importance of SIC4 industry j in states classified as swing during term T (see equation (4)). The inclusion of sector fixed effects at the SIC4 level (δ_j) allows us to control for any time-invariant characteristic that may affect the extent to which an industry is protected. We also include term fixed effects (δ_T) to account for time-varying macroeconomic and political conditions. In line with earlier studies (e.g., Pierce and Schott, 2016), we weight regression estimates by pre-sample (1988) industry employment to account for heterogeneity in the size of SIC4 industries. We cluster standard errors at the

[27] Notice that, if voters were fully rational (no reciprocity), electoral incentives could not affect trade policy, since their decisions would not depend on past policy choices.

[28] In Conconi *et al.* (2017), the trade policy choice is the initiation of trade disputes. The same logic applies to AD duties. The main difference is that US presidents can directly initiate trade disputes, while AD decisions are taken by the DOC and the ITC. However, as discussed before, the president can influence these decisions: he can directly affect AD rulings of the DOC, which is part of the executive branch (top officials are directly nominated by the president); he can also affect votes of ITC commissioners, who are known to be influenced by political pressure (e.g., Aquilante, 2018).

SIC3 level (221 industries) to allow for correlated industry shocks.

The coefficient β_1 is identified under the assumption of a random assignment of the treatment variable *Swing Industry*$_{j,T}$. In turn, this implies assuming that (i) the state-level political shocks (captured by the variable *Swing State*$_{s,T}$) are i.i.d. across all presidential terms; and (ii) the pre-sample distribution of industries across states (captured by the variable $L_{s,j}$) generates exogenous variation in exposure to these shocks.

Table 1 reports the results of estimating (5) for first terms. In column 1, we use our baseline definitions of *Trade Protection*$_{j,T}$ and *Swing Industry*$_{j,T}$. As expected, β_1 is positive and significant, indicating that the level of protection granted to an industry during executive first terms depends on its importance in swing states. The estimates in column 1 imply that a one standard deviation (0.001) increase in *Swing Industry*$_{j,T}$ increases the level of trade protection by 0.4 percentage points, explaining 18% of the average protection in our sample (2.1%).

The rest of the table reports the results of a series of robustness checks. In column 2, we include all temporary trade barriers against China (AD duties, countervailing duties, and safeguards) when computing the share of protected products in the industry. In column 3, we use a simple indicator variable to capture the extensive margin of AD protection. In column 4, we modify the definition of the variable *Swing Industry*$_{j,T}$, constructing the denominator based only on employment in manufacturing sectors. In column 5, we use data on the outcome of the presidential elections at the end of a term to define the states expected to be swing in that term. In column 6, we exclude the first term of Donald Trump from the sample period. The coefficient of *Swing Industry*$_{j,T}$ remains positive and significant in all specifications. Notice that the coefficients in columns 3 and 5 are different in size compared to the rest of the table. However, the magnitude of the effects are similar once we take into account the higher mean of the alternative AD measure (13.9%) and the higher standard deviation of *Swing Industry*$_{j,T}$ (0.004) in these two specifications respectively. Figure A-3 in the Appendix shows that the results of Table 1 are also robust to dropping each SIC2 industry (panel (a)) and each term (panel (b)) at a time. This reveals that the results are not driven by heavy AD-using industries such as steel (within SIC33) or measures imposed during a particular presidential term.

Table 1
Swing-State Politics and AD Protection

	Baseline	All TTBs	AD dummy	Pres. elections	Manuf. industries	Excluding Trump
	(1)	(2)	(3)	(4)	(5)	(6)
Swing Industry$_{j,T}$	3.857**	3.807**	43.110***	3.313**	0.879**	3.816**
	(1.548)	(1.726)	(9.093)	(1.587)	(0.356)	(1.495)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.49	0.5	0.56	0.49	0.49	0.50
Observations	1,960	1,960	1,960	1,960	1,960	1,568

The table reports OLS estimates of equation (5). In columns 1, 4, 5 and 6, the dependent variable is *Trade Protection*$_{j,T}$, the share of HS6 products within SIC4 industry j that are subject by AD duties during term T; in column 2, it is the share of products subject to any temporary trade barrier (AD duties, countervailing duties, or safeguards); in column 3, it is a dummy variable equal to 1 if any product in industry j is subject to AD duties. The variable *Swing Industry*$_{j,T}$ is defined in equation (4). In columns 1-4 and 6, the denominator of this variable includes all industries; in column 5, it includes only manufacturing industries. In columns 1-3 and 5-6 (column 4), swing states are identified using data on the outcome of congressional (presidential) in the middle (at the end) of term T. In columns 1-5 (column 6), the sample covers all executive first terms during 1989-2020 (1989-2016). Observations are weighted by 1988 employment. Sector fixed effects are defined at the SIC4 level. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-6 in the Appendix shows that swing-state politics has no effect on AD protection during second terms, when the incumbent president is a lame duck: the coefficient of the variable *Swing Industry*$_{j,T}$ is not significant in any of the specifications.[29] Comparing Tables 1 and A-6 shows that the level of AD protection granted to an industry depends on its importance in swing states, but only during executive first terms, when the president can be re-elected.[30]

[29]This table does not include column 6 of Table 1, given that President Trump was in office only for one term. Notice that the number of observations in columns 1-5 of Table A-6 is lower than in the corresponding specifications of Table 1. This is because, in addition to Trump, Bush senior was in office for only one term. This is, however, not the reason behind the difference in the results: if we drop the 1989-1992 term, the coefficient of *Swing Industry*$_{j,T}$ remains positive and significant in first terms (see panel (b) of Figure A-3).

[30]We have also estimated yearly regressions to examine whether the effects of swing-state politics on trade protection vary within first terms. We find no evidence of significant differences across years. This is not surprising given the institutional process described in Section 3: while the president can influence AD decisions taken by the DOC and the ITC, it cannot directly control the timing of their rulings.

5.2 Addressing Identification Concerns

In what follows, we provide additional evidence to support the causal interpretation of the results presented in the previous section.

One may be concerned about the exogeneity of the political shocks. For this reason, our baseline definition of $\textit{Swing State}_{s,T}$ exploits variation in the outcome of midterm House elections (rather than presidential elections). Moreover, in Appendix A-3 we show that the identity of swing states is uncorrelated with various state-level characteristics (the extent to which industries in the state have been exposed to trade protection and import competition, and the degree to which employment has been declining).

Even if the state-level shocks are random, industry exposure may not be: the pre-sample spatial distribution of industries (captured by $L_{s,j}$) may be correlated with unobservable industry characteristics that affect the level of trade protection. In this case, the estimates of Table 1 would suffer from an omitted variable bias (OVB). To address this concern, we first carry out placebo tests by randomizing the identity of swing states and show that the results of Table 1 are robust to applying the "recentering" methodology proposed by Borusyak and Hull (2023). We then present the results of difference-in-differences regressions, in which we can relax the assumption that $\textit{Swing Industry}_{j,T}$ is randomly assigned.

5.2.1 Placebo Tests

To carry out placebo tests, we randomize the identity of swing states across the 36 states that were classified as swing at least once during the period 1989-2020. We consider two sets of counterfactual shocks. First, we fix the number of times in which a state is swing to be the same as in Figure 2 (e.g., 5 for Illinois, 4 for Michigan, 3 for Colorado, 2 for Ohio, 1 for Arizona) and randomize across terms. We perform 1,000 randomizations, each consisting of independent random draws of swing states for each presidential term. From each randomization, we obtain a variable $\textit{Placebo Swing State}^{1}_{s,T}$.

The second set of counterfactual shocks is generated by keeping the number of swing states in a given term to be as in Figure 2 (e.g., 7 for the term ending in 2004, 9 for the term ending in 2008, 6 for the term ending in 2012) and randomize across the 36 states that were classified as swing at least once during our sample period. Again, we perform 1,000 randomizations, from which we obtain the variable $\textit{Placebo Swing State}^{2}_{s,T}$.

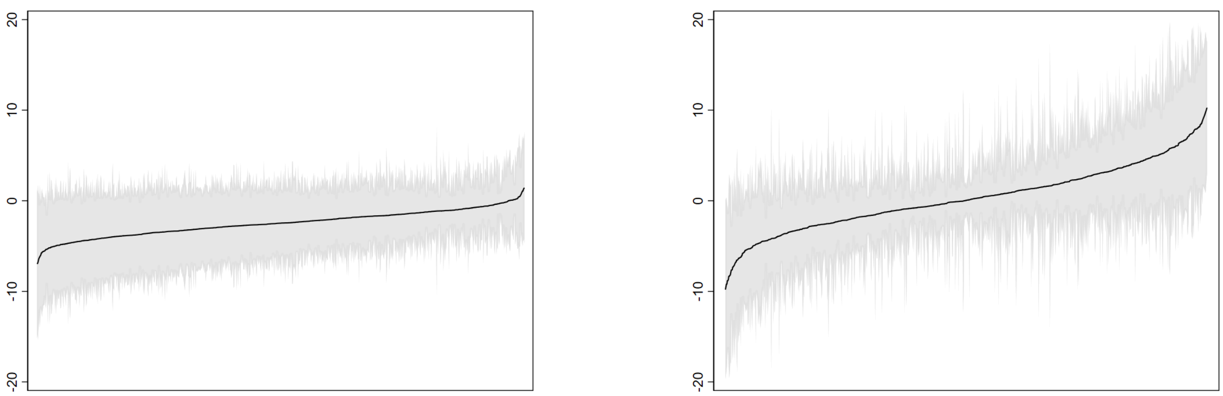
To carry out the placebo tests, we re-estimate (5) replacing $\textit{Swing Industry}_{j,T}$ with $\textit{Placebo Swing Industry}^{1}_{j,T}$ or $\textit{Placebo Swing Industry}^{2}_{j,T}$.[31] Figure 3 shows the distribution

[31]The variable $\textit{Placebo Swing Industry}^{1}_{i,T}$ ($\textit{Placebo Swing Industry}^{2}_{i,T}$) is constructed by replacing the

of the 1,000 estimated β_1 coefficients with their 99% confidence intervals for the two types of placebo tests. Randomizing the identity of swing states produces a wide range of coefficients, only a minority of which are positive and significant.[32] Comparing these findings with the results of Table 1 shows that it is crucial to use information on the states expected to be swing in a *given* electoral term to predict the level of trade protection in that term.

Figure 3

Estimated Coefficients of *Placebo Swing Industry*$_{j,T}$



(a) (b)

The figure plots the β_1 coefficients (with 99% confidence intervals) obtained by estimating (5) and replacing *Swing Industry*$_{j,T}$ with *Placebo Swing Industry*$^1_{j,T}$ (panel (a)) or *Placebo Swing Industry*$^2_{j,T}$ (panel (b)).

Using the placebo treatment variables, we can apply the recentering methodology proposed by Borusyak and Hull (2023) to address concerns about non-random industry exposure to the state-level shocks. By averaging across the 1,000 randomizations of swing states describe above, we obtain the variables *Expected Swing Industry*$^1_{j,T}$ and *Expected Swing Industry*$^2_{j,T}$, which we subtract from *Swing Industry*$_{j,T}$ to recenter the baseline estimates of Table 1. Table 2 shows that the results on the effects of swing-state politics are robust to addressing concerns about OVB: the estimates are not statistically different from the baseline coefficient of *Swing Industry*$_{j,T}$ in column 1 of Table 1.

dummy variable *Swing State*$_{s,T}$ in equation (4) with *Placebo Swing State*$^1_{s,T}$ (*Placebo Swing State*$^1_{s,T}$).

[32]The coefficients of *Placebo Swing Industry*$^1_{i,T}$ (*Placebo Swing Industry*$^2_{i,T}$) are positive and significant at the 5% level in only 17% (19%) of the cases. In panel (a), the coefficient of *Placebo Swing Industry*$^1_{j,T}$ ranges from -6.966 to 1.432, with mean -2.504. In panel (b), the coefficient of *Placebo Swing Industry*$^2_{j,T}$ ranges from -9.812 to 10.290, with mean 0.228.

Table 2

Swing-State Politics and AD Protection

(Recentered *Swing Industry*$_{j,T}$)

	Counterfactual shocks 1	Counterfactual shocks 2
	(1)	(2)
Swing Industry$_{j,T}$	4.082**	3.814**
	(1.611)	(1.563)
Sector FE	Yes	Yes
Term FE	Yes	Yes
Adjusted R^2	0.50	0.49
Observations	1,960	1,960

The table reports OLS estimates of equation (5). The dependent variable is *Trade Protection*$_{j,T}$, the share of HS6 products within SIC4 industry j that are subject by AD duties during term T. The variable *Swing Industry*$_{j,T}$ is defined in equation (4). In column 1 (column 2), we recenter this variable using *Expected Swing Industry*$^1_{j,T}$ (*Expected Swing Industry*$^2_{j,T}$). The sample covers all executive first terms during 1989-2020. Observations are weighted by 1988 employment. Sector fixed effects are defined at the SIC4 level. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

5.2.2 Difference-in-Differences Regressions

Our empirical analysis builds on the theoretical model by Conconi *et al.* (2017), which underscores the influence of swing-state politics on US trade policy when the president can be re-elected. The results presented in Section 5.1 provide empirical support for this prediction assuming that *Swing Industry*$_{j,T}$ is randomly assigned. In what follows, we present the results of difference-in-differences (DID) regressions, which allow us to relax this assumption.

As an illustration, consider a president's first term ($T = 1$) and the preceding term ($T = 0$). We can define the variable *Swing Industry*$^{DID}_{j,T}$ to be equal to *Swing Industry*$_{j,T}$ in $T = 1$, and 0 in $T = 0$. We aim to estimate the effect of being a key industry in states expected to be swing when the president can be re-elected. The average treatment effect on the treated can be estimated with a standard two-way fixed effects DID model:

$$Trade\ Protection_{j,T} = \beta_0 + \beta_1 Swing\ Industry^{DID}_{j,T} + \delta_j + \delta_T + \epsilon_{j,T}. \tag{6}$$

In this setting, the β_1 coefficient is identified under the parallel trend assumption, i.e., the trend in mean untreated outcomes must be independent of the observed treatment status. This assumption implies that any differences observed post-treatment are attributable to the impact of swing-state politics.

We can extend the model defined in (6) to all presidencies to capture the impact of swing-states politics on trade policy in different first terms:

$$\textit{Trade Protection}_{j,T(p)} = \beta_0 + \beta_1 \textit{Swing Industry}^{DID}_{j,T(p)} + \delta_{j,p} + \delta_{T(p)} + \epsilon_{j,T(p)}. \tag{7}$$

The variable *Swing Industry*$_{j,p}$ captures the importance of industry j in states expected to be swing during the first term of president p. *Swing Industry*$^{DID}_{j,T(p)}$ is equal to the value of *Swing Industry*$_{j,T}$ for the first term of each presidency p ($T(p) = 1$) and zero for the preceding term ($T(p) = 0$). It reflects the exposure of industry j to swing-state politics during the first term of each presidency. Crucially, the DID specification allows us to include (linear) industry-level trends at the SIC4 level $\delta_{j,p}$ to address concerns about omitted variables that may be correlated with *Swing Industry*$^{DID}_{j,T(p)}$ and *Trade Protection*$_{j,T(p)}$. The $\delta_{T(p)}$ fixed effects account for macroeconomic and political shocks common to all industries.

The estimates of (7) are presented in Table 3. In column (1), we present the results of the two-period DID model and find a positive estimate that is statistically significant at the 10% level. In column 2, we further account for non-linear industry trends at the broader (SIC2) level, by replacing $\delta_{T(p)}$ in (7) with $\delta_{T(p),k}$ fixed effects (where k is the SIC2 industry containing SIC4 industry j). The coefficient of *Swing Industry*$_{j,p}$ is positive and highly significant, confirming that swing-state politics affects the level of trade protection during executive first terms.

Table 3

Swing-State Politics and AD Protection (DID)

	One pre-treatment period		Two pre-treatment periods	
	(1)	(2)	(3)	(4)
Swing Industry$^{DID}_{j,T(p)}$	1.20*	1.41***	1.88**	1.96***
	(0.62)	(0.52)	(0.73)	(0.70)
President-SIC4 FE	Yes	Yes	Yes	Yes
Term FE	Yes	No	Yes	No
Term-SIC2 FE	No	Yes	No	Yes
Adjusted R^2	0.86	0.87	0.84	0.86
Observations	3,136	3,136	3,528	3,528

The table reports OLS estimates of equation (7). The dependent variable is *Trade Protection*$_{j,T(p)}$, the share of HS6 products in SIC4 industry j subject to AD duties during the first term of president p. The variable *Swing Industry*$_{j,p}$ is the value of *Swing Industry*$_{j,T}$ during the first term of president p. Observations are weighted by 1988 employment. Sector fixed effects are defined at the SIC4 level. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

We next extend the pre-trend period of each president. We thus modify our benchmark DID model with $T(p) = -1, 0, 1$ for each president p (e.g., the two terms of Obama are pre-treatment periods for Donald Trump).[33] The results are reported in columns (3) and (4) of Table 3. The estimated coefficient β_1 remains positive and significant (at least at the 5% level) with and without including $\delta_{T(p),k}$ fixed effects.

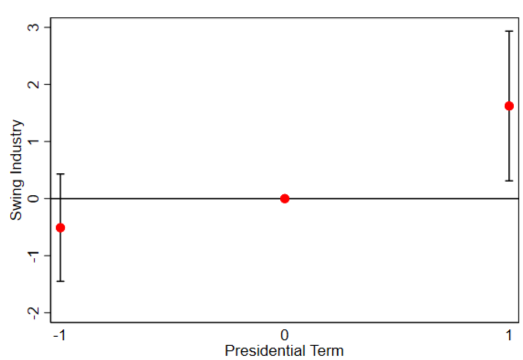
We can also study dynamic treatment effects to run a pre-trend test, by carrying out the following event study:[34]

$$\textit{Trade Protection}_{j,T(p)} = \sum_{\substack{\tau=-1 \\ \tau\neq 0}}^{1} \beta_\tau \textit{Swing Industry}_{j,p} \times I_{\{T=\tau\}} + \delta_{j,p} + \delta_{T(p),k} + \epsilon_{j,T,p}, \tag{8}$$

where $I_{\{T(p)=\tau\}}$ is a dummy variable identifying the first term of president p and the two terms before. The coefficients β_τ measure the dynamic treatment effects. We normalize $\beta_0 = 0$, so the estimated coefficients are relative to the term before the start of a presidency.

Figure 4

Event Study



The figure reports the results of estimating (8). 90% confidence intervals are based on standard errors clustered at the SIC3 level.

The results reported in Figure 4 confirm that swing-state politics affects trade protection during first terms (β_τ is significant in period 1). The coefficient estimating the pre-trend

[33]For each president, we thus have two pre-treatment periods. Notice that the first terms of Bush Sr. and Bill Clinton cannot be included as treatment periods, since the corresponding pre-treatment periods are outside our 1989-2020 sample. The qualitative results of Table 3 continue to hold if we shorten the pre-treatment period to one term and include the presidency of Bill Clinton.

[34]A recent literature surveyed by de Chaisemartin and D'Haultfœuille (2023) emphasizes that estimating event studies with a two-way fixed-effects estimator may fail to recover the treatment effect when the roll-out is staggered. This is not a concern in our setting, in which treatment always occurs during first terms.

(β_{-1}) is not significantly different from zero supporting the parallel trend assumption and therefore the causal interpretation of our findings about the effects of swing-state politics on trade protection.

5.3 Micro-Level Evidence on Swing-State Politics and AD Votes

In this section, we examine whether swing-state politics affects AD decisions of ITC commissioners. As discussed in Section 3, the ITC is composed of six commissioners nominated by the President and confirmed by the Senate, who vote on whether the petitioning industry has been materially injured by imports from the targeted country. If at least half of the votes are positive, then the AD duty is introduced. ITC commissioners are appointed for nine years, during which they cast many votes involving different industries. Previous work shows that these votes are influenced by political pressure (e.g., Aquilante, 2018).

To provide micro-level evidence behind the results of Table 1, we collect all final ITC votes on AD cases against China during 1989-2020 and estimate the following regression on executive first terms:[35]

$$Vote_{i,c(j),t(T)} = \beta_0 + \beta_1 Swing\ Industry_{j,T} + \delta_{i,j} + \delta_{i,t} + \varepsilon_{i,c(j),t(T)}. \tag{9}$$

$Vote_{i,c(j),t(T)}$ is a dummy variable equal to 1 if ITC commissioner i votes in favor of AD duties on case c (involving SIC4 industry j) in year t (during presidential term T). The variable $Swing\ Industry_{j,T}$ defined before captures the importance of an industry in states expected to be swing during electoral term T. In our preferred specification, we fully saturate the model, including commissioner-industry fixed effects ($\delta_{i,j}$) and commissioner-year fixed effects ($\delta_{i,t}$), which account for the role of unobservable commissioner characteristics interacted with time dummies to account for macroeconomic and political conditions. In this specification, we exploit variation in the voting behavior of individual commissioners in cases involving the same petitioning industry; the β_1 is identified by variation in $Swing\ Industry_{j,T}$ driven by the state-level political shocks.

[35] In line with the rest of our analysis, we consider votes on AD cases in which China is the target country. The results are robust to excluding the presidency of Donald Trump.

Table 4

Swing-State Politics and AD Votes

	(1)	(2)
Swing Industry$_{j,T}$	60.943**	62.905**
	(26.311)	(26.551)
Commissioner-Sector FE	Yes	Yes
Commissioner-Year FE	Yes	No
Year FE	No	Yes
Adjusted R^2	0.22	0.35
Observations	534	557

Column 1 reports OLS estimates of equation (9) during the 1989-2020 period. In column 2, we replace Commissioner-Year FE with Year FE. Observations are weighted by 1988 employment. Sector fixed effects are defined at the SIC4 level. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Column 1 of Table 4 reports the results of estimating (9) for our main sample period. The estimated β_1 coefficient implies that a one standard deviation (0.002) increase in *Swing Industry*$_{j,T}$ increases the probability that an ITC commissioner votes in favor of the petitioning industry by 12 percentage points, which corresponds to 15% of the average probability of a positive vote in the sample (79%). Column 2 shows that the results are robust to replacing commissioner-year fixed effects with year fixed effects. Notice that the number of observations increases slightly in this less demanding specification.

In line with our findings on the level of trade protection, swing-state politics does not affect the voting behavior of ITC commissioners during second terms, when the executive cannot be re-elected: if we estimate (9) on second terms, the coefficient of the variable *Swing Industry*$_{j,T}$ is not significant.[36]

6 Effects of Politically Motivated Trade Protection

In this section, we study the effects of trade protection driven by swing-state politics. As pointed out by Trefler (1993), endogeneity poses a key challenge to identify the impact of trade policies. Ordinary least squares (OLS) would not be able to identify causal effects

[36] These results are available upon request.

because of omitted variable bias. For example, positive productivity shocks to foreign exporters, or negative productivity shocks to domestic producers, can be correlated with both employment growth and trade protection. Omitting these variables from an OLS regression would cause estimates of the direct effects of protection on employment to be negatively biased, making it harder to identify the positive effects of AD duties on protected industries.

When studying the effects along supply chains, a major concern is the presence of unobservables correlated with the level of protection and the performance of downstream industries. For example, a positive productivity shock experienced by foreign input suppliers should foster growth in US downstream sectors. The same shock can also lead to increased input protection: in AD investigations, a surge in imports makes it more likely that the industry petitioning for protection passes the injury test. Omitting these shocks would thus bias the estimated OLS coefficients downward, working against finding adverse effects of trade protection on downstream industries.

6.1 An Instrument for Politically Motivated Trade Protection

To identify the effects of trade protection, we construct a shift-share instrument, studying the impact of a set of shocks (or "shifters") on units differentially exposed to them, with the exposure measured by a set of disaggregate weights (or "shares").[37]

In our setting, the shifters are political shocks driven by changes in the identity of swing states across electoral terms, captured by the variable $\textit{Swing State}_{s,T}$. Figure 2 above illustrates the variation in this variable based on the outcome of midterm House elections. As discussed above, we assume that the state-level political shocks are i.i.d. across terms. The placebo tests carried out in Section 5.2.1 show that predicting the level of trade protection granted to an industry during a presidential term requires using information on the identity of swing states in that term.

To capture heterogeneous industry exposure to state-level shocks, we use different variables. Some have already been defined above: the pre-sample employment levels $L_{s,j}$ are used to measure the importance of an industry in swing states (see equation (4)), and the input-output coefficients $\omega_{i,j}$ and θ_{ij} are used to capture vertical linkages between industries (see equations (2) and (3)).

To address concerns about the exclusions restriction, we further exploit heterogeneity across industries in their historical experience in AD proceedings. As stressed by Blonigen

[37]See Bartik (1991) for an early application of this research design and Adão *et al.* (2020), Goldsmith-Pinkham *et al.* (2020), Borusyak *et al.* (2022), and Borusyak and Hull (2023) for recent contributions on the statistical properties of shift-share instruments.

(2006), the process of petitioning for AD duties is extremely complex (see Section 3 and footnote 17). As a result, prior experience in petitioning plays an important role in AD filings and outcomes.[38] Building on these arguments, we construct the variable $\textit{AD Experience}_j$, which is the count of the petitions filed by industry j before the start of our sample.[39] As pointed out by Irwin (2005), during the 1980s, legal and institutional changes in AD proceedings made it easier to file for AD protection, leading to a steep increase in the number of AD petitions. However, some industries did not need to file for AD, since they were already protected by other policies (e.g., voluntary export restraints, the Multi-Fibre Arrangement). Indeed, the experience variable is positive for only 45% of manufacturing industries.[40]

In the empirical analysis carried out in Section 6.2, we fix all industry exposure shares (employment, input-output coefficients, and AD experience) before or at the start of our sample period. Although we control for these shares by including industry fixed effects, one may be concerned about non-random industry exposure to the shocks, which could give rise to an OVB in the 2SLS estimates. To address this concern, in Section 6.2, we show that the results are robust to applying the "recentering" methodology of Borusyak and Hull (2023).

To predict the level of protection granted to industry j during term T, we use the variable:

$$IV_{j,T} = \textit{Swing Industry}_{j,T} \times \textit{AD Experience}_j. \tag{10}$$

This instrument is the interaction between an industry's (time-varying) importance in swing states, captured by the variable $\textit{Swing Industry}_{j,T}$, and its (time-invariant) historical experience in AD proceedings, captured by the variable $\textit{AD Experience}_j$.

An alternative strategy would be to simply use the variable $\textit{Swing Industry}_{j,T}$ defined in equation (4) as the instrument. However, by itself, the variable $\textit{Swing Industry}_{j,T}$ could capture the effects of other policies that may be used to favor key industries in swing states (e.g.,

[38]Blonigen (2006) shows that previous experience lowers future filing costs and increases petitioners' effectiveness in arguing their case, increasing the probability of favorable outcomes.

[39]We include all petitions between 1980 (the first year for which the data is available) and 1987. We exclude petitions filed in 1988, which led to investigations during our sample period.

[40]In line with Blonigen (2006), the number of petitions filed by an industry depends crucially on its previous experience: the correlation between the number of petitions filed by SIC4 industry j during our sample period and $\textit{AD Experience}_j$ is 0.855 and significant at the 1% level. Blonigen finds that prior AD experience is also associated with lower dumping margins and interprets this result as suggesting that experience lowers filing costs, leading to the filing of weaker cases. In our sample period, we find instead that the correlation between $\textit{AD Experience}_j$ and the average dumping margin of cases filed by industry j is actually positive (0.199) and significant at the 1% level.

federal subsidies), thus violating the exclusion restriction. Interacting $Swing\ Industry_{j,T}$ with $AD\ Experience_j$ makes the instrument AD specific,[41] alleviating concerns about the exclusion restriction.

The logic behind our instrument is that AD protection should be skewed in favor of industries that are important in swing states, but only if they can exploit this political advantage thanks to their prior knowledge of the complex procedures to petition for AD duties. In line with this idea, sectors like "Blast furnaces and steel mills" (SIC 3312) and "Motor vehicle parts and accessories" (SIC 3714), which score highly both in terms of average political importance in swing states and historical experience in filing for AD duties (see Table A-3), are among the most protected. Instead, sectors such as "Newspapers" (SIC 2711) and "Search and navigation equipment" (SIC 3812), which score highly in terms of average $Swing\ Industry_{j,T}$ but have no historical experience in AD, receive no AD protection (see Table A-3).

We next show that our instrument is a strong predictor of the level of AD protection granted to industry j during electoral term T. To this purpose, we estimate:

$$Trade\ Protection_{j,T} = \beta_0 + \beta_1 IV_{j,T} + \delta_j + \delta_T + \varepsilon_{j,T}. \tag{11}$$

Table 5 reproduces the same specifications of Table 1, replacing the variable $Swing\ Industry_{j,T}$ with $IV_{j,T}$. The estimated coefficient of this variable is positive and significant at the 1% level in all specifications.

One may be concerned that the results could be driven by the steel industry (SIC 3312), which is an outlier in terms of its historical AD experience (see Table A-3). We have verified that the coefficient of $IV_{j,T}$ remains positive and significant if we drop this industry or winsorize the experience variable before constructing the instrument. More generally, the results are robust to dropping from our sample each SIC2 industry and each presidential term.[42]

Comparing the estimates of Table 5 with the corresponding estimates of Table 1 shows that combining $Swing\ Industry_{j,T}$ with $AD\ Experience_j$ increases the predictive power of the instrument. For example, in our baseline specification, the coefficient of $IV_{j,T}$ is positive and significant at the 1% level (compared to the 5% level for the corresponding coefficient of $Swing\ Industry_{j,T}$ in Table 1). This finding is in line with Blonigen (2006)'s argument that

[41] Notice that the instrument takes into account the importance of an industry in swing states only to the extent that the industry has some experience at filing AD petitions.

[42] These results are available upon request.

industries' long-term knowledge of the complex AD proceedings is an important determinant of AD protection. In terms of magnitude, column 1 indicates that a one standard deviation (0.013) increase in $IV_{j,T}$ increases the level of protection by 0.5 percentage points, explaining 25% of the average level of protection (2.1%).

Table 5

IV and AD Protection

	Baseline	All TTBs	AD dummy	Pres. elections	Manuf. industries	Excluding Trump
	(1)	(2)	(3)	(4)	(5)	(6)
$IV_{j,T}$	0.413***	0.451***	2.986***	0.339***	0.091***	0.340***
	(0.054)	(0.074)	(0.512)	(0.019)	(0.011)	(0.041)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.50	0.50	0.56	0.50	0.50	0.51
Observations	1,960	1,960	1,960	1,960	1,960	1,568

The table reports OLS estimates of equation (11). In columns 1, 4, 5 and 6, the dependent variable is *Trade Protection*$_{j,T}$, the share of HS6 products in SIC4 industry j that are subject by AD duties during term T; in column 2, it is the share of products subject to any temporary trade barrier (AD duties, countervailing duties, or safeguards); in column 3, it is a dummy variable equal to 1 if any product in industry j is subject to AD duties. The variable $IV_{j,T}$ is defined in equation (10). In columns 1-4 and 6, the denominator of the variable *Swing Industry*$_{j,T}$ used to construct $IV_{j,T}$ includes all industries; in column 5, it includes only manufacturing industries. In columns 1-3 and 5-6 (column 4), swing states are identified using data on the outcome of congressional (presidential) in the middle (at the end) of term T. In columns 1-5 (column 6), the sample covers all executive first terms during 1989-2020 (1989-2016). Observations are weighted by 1988 employment. Sector fixed effects are defined at the SIC4 level. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-7 in the Appendix shows that the coefficient of $IV_{j,T}$ remains positive and significant at the 1% level if we further include the variable *Swing Industry*$_{j,T}$ not interacted with AD experience. Interestingly, the coefficient of this variable is positive but insignificant in most specifications. This finding suggests that industries that are important in swing states are granted higher protection, but only if they have some historical experience at petitioning for AD duties.

6.2 Distributional Effects of Politically Motivated Protection

We next use our instrument to examine the effects of politically motivated trade protection, focusing on employment (the effects on imports are examined in Appendix Section A-4). We show that trade protection generates winners and losers along supply chains: it fosters employment growth in protected industries, but hinders employment growth in downstream industries.

To examine the effects on directly exposed sectors, we consider all manufacturing industries and estimate the following regression by 2SLS:

$$\Delta L_{j,T} = \beta_0 + \beta_1 \textit{Direct Tariff Exposure}_{j,T} + \beta_2 \textit{Swing Industry}_{j,T} + \delta_j + \delta_T + \varepsilon_{j,T}, \tag{12}$$

where $\Delta L_{j,T}$ is the growth rate of employment in SIC4 industry j during term T.[43] In all specifications, we include SIC4 sector and term fixed effects (δ_j and δ_T). Notice that, since the dependent variable is expressed in differences, the sector fixed effects allow us to control for (linear) sectoral trends (e.g., the extent to which an industry is declining or being automated). The tariff exposure variable is defined in equation (1) and is instrumented by $IV_{j,T}$.[44] To account for the effects of other policies that may be used to favor important industries in swing states (e.g., federal subsidies), we include the variable *Swing Industry*$_{j,T}$ not interacted with AD experience.

To study whether the effects of trade protection propagate along supply chains, we consider all sectors in the economy and estimate:

$$\begin{aligned}\Delta L_{j,T} \;=\;& \beta_0 + \beta_1 \textit{Downstream Tariff Exposure}_{j,T} + \beta_2 \textit{Upstream Tariff Exposure}_{j,T} \\ &+ \beta_3 \textit{Downstream Swing Industry}_{j,T} + \beta_4 \textit{Upstream Swing Industry}_{j,T} + \delta_j + \delta_T + \varepsilon_{j,T},\end{aligned} \tag{13}$$

where indirect tariff exposure variables are defined in equations (2)-(3) and are instrumented with the corresponding IV measures.[45] In alternative specifications, we construct these measures accounting for only direct or for both direct and indirect input-output linkages and including or excluding the diagonal of the input-output matrix. To account for the effects of other federal policies that may be affected by swing-state politics, we control for the corresponding swing industry variables not interacted with AD experience.[46] Several studies

[43] For the term T ending in year t, $\Delta L_{j,T} = \ln(\textit{Employment}_{j,t}) - \ln(\textit{Employment}_{j,t-4})$. In line with the analysis in Section 5.1, we focus on the effects during executive first terms, when the president has incentives to manipulate trade policy for re-election purposes.

[44] Note that, even though this variable is expressed in levels, its variation reflects policy changes (the imposition of new AD duties and the revocation or renewal of old duties).

[45] Downstream exposure is instrumented by *Downstream* $IV_{j,T} \equiv \sum_{i=1}^{N} \omega_{i,j} IV_{i,T}$, and the upstream exposure by *Upstream* $IV_{j,T} \equiv \sum_{i=1}^{N} \theta_{i,j} IV_{i,T}$. Notice that the variable *Direct Tariff Exposure* cannot be included in these regressions, since it cannot be defined for non-tradable industries.

[46] These variables are defined as *Downstream Swing Industry*$_{j,T} \equiv \sum_{i=1}^{N} \omega_{i,j}$ *Swing Industry*$_{i,T}$ and *Upstream Swing Industry*$_{j,T} \equiv \sum_{i=1}^{N} \theta_{i,j}$ *Swing Industry*$_{i,T}$.

show that the special tariffs introduced by Donald Trump — and the resulting retaliatory tariffs imposed by other countries — had employment effects on industries directly and indirectly exposed to them (e.g., Flaaen and Pierce, 2022). To isolate the effects of politically motivated AD protection, we thus exclude the presidency of Donald Trump for our baseline 2SLS regressions.

Table 6

Effects of Trade Protection on Employment Along Supply Chains

	Manufacturing industries	All industries			
		including diagonal		excluding diagonal	
	(1)	(2)	(3)	(4)	(5)
Direct Tariff Exposure$_{j,T}$	4.213**				
	(1.963)				
Downstream Tariff Exposure$_{j,T}$		-3.648**	-3.023**	-3.235**	-2.922*
		(1.651)	(1.470)	(1.637)	(1.524)
Upstream Tariff Exposure$_{j,T}$		4.441**	2.783**	3.338	2.037
		(1.783)	(1.176)	(2.652)	(1.497)
Sector Fixed Effects	Yes	Yes	Yes	Yes	Yes
Term Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,567	1,915	1,915	1,915	1,915
KP F-statistic	22.4	20.7	33.1	15.4	18.9

The table reports 2SLS estimates of equations (12) and (13). The dependent variable $\Delta L_{j,T}$ is the log change in employment in SIC4 industry j during term T. The tariff variables capture exposure to AD protection, as measured by (1)-(3), instrumented using the corresponding IV variables. In columns 2 and 3, the downstream and upstream measures include the diagonal of the input output-matrix and respectively account for direct linkages only or also for higher-order linkages; in columns 4 and 5, they exclude the diagonal of the input-output matrix and respectively account for direct linkages only or also for higher-order linkages. The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). The sample covers all first terms during 1989-2016 and includes all manufacturing industries (all industries) in column 1 (columns 2-5). Observations are weighted by 1988 employment. Sector fixed effects are defined at the SIC4 level. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

The results of estimating (12) and (13) are reported in Table 6. The coefficient of *Direct Tariff Exposure*$_{j,T}$ in column 1 is positive and significant, indicating that AD duties foster employment growth in protected industries. In term of magnitude, our estimate implies that a one standard deviation (0.014) increase in predicted trade protection increases employment growth by 5.9 percentage points, explaining around 27% of the standard deviation of employment growth in those industries.

Looking at the effects along supply chains, the coefficient of *Downstream Tariff Exposure*$_{j,T}$ is always negative and significant, indicating that AD duties decrease the employment growth rate of industries that use the protected goods as inputs. Our preferred specification is column 4, which is based on direct input-output linkages and excludes the diagonal of the input-output matrix to isolate the indirect effects of protection. Based on this specification, a one standard deviation (0.007) increase in predicted *Downstream Tariff Exposure*$_{j,T}$ decreases the employment growth rate by 2.3 percentage points, explaining around 10% of the standard deviation of employment growth in downstream industries.

The coefficient of *Upstream Tariff Exposure*$_{j,T}$ is positive and significant when we construct this measure including the diagonal of the input-output matrix (columns 2-3), but becomes insignificant when we exclude the diagonal to isolate the indirect effects of trade protection (columns 4-5). These results suggest that the positive effects of trade protection are confined to protected industries.

The last row of Table 6 reports the Kleibergen-Paap (KP) F-statistics, a version of the Cragg-Donald statistic adjusted for clustered robust standard errors. These are well above the critical value of 16 (with one endogenous variable) and 7 (with multiple endogenous variables) based on a 10% maximal IV size, indicating that our instruments are strong.[47]

It should be stressed that the estimates in Table 6 capture local average treatment effects for the "compliers," the subset of industries in the sample that takes the treatment if and only if they were assigned to it (Imbens and Angrist, 1994). We are thus capturing the effects of politically-driven protectionist measures identified by our instrument. It is also noteworthy to compare the 2SLS estimates of Table 6 with the corresponding OLS estimates in Table A-8. As discussed at the start of this section, we expect the OLS estimates to be downward biased (in absolute value) due to omitted variables. In line with this argument, the coefficient of *Direct Tariff Exposure*$_{j,T}$ in Table A-8 is close to zero and not statistically significant; and the coefficients of *Downstream Tariff Exposure*$_{j,T}$ are smaller in magnitude compared to Table 6.

[47] The instruments are positive and significant at the 1% level in the first stage. The reduced-form regressions can be found in Table A-9; the coefficients of the instruments have the same signs as in Table 6 (e.g., in the first-stage of column 1, the estimated coefficient of $IV_{j,t}$ is 0.302, significant at the 1% level).

Robustness Checks

We have carried out a series of additional estimations to verify the robustness of the results of Table 6. First, one may be concerned about the endogeneity of the shares in our shift-share instrument. For example, an industry's historical experience in AD proceedings may be correlated with other potential drivers of employment growth. Even if the political shocks are as-good-as randomly assigned, non-random exposure to the shocks would give rise to an omitted variable bias in our 2SLS estimates.

To address this concern, we apply the "recentering" methodology proposed by Borusyak and Hull (2023), subtracting from our IV variables the "expected instruments" created by randomizing the identity of swing states. As in Section 5.2.1, we consider the 36 states classified as swing at least once during our sample period and construct two types of counterfactual shocks. In the first, we fix the number of times in which a state is swing to be the same as in Figure 2 (e.g., 5 for Illinois, 4 for Michigan, 3 for Colorado, 2 for Ohio, 1 for Arizona) and randomize the identity of swing states across terms. We perform 1,000 randomizations of swing states, consisting of independent random draws of swing states for each presidential term. From each randomization, we obtain a variable $\textit{Placebo Swing State}^1_{s,T}$, which we use to construct $\textit{Placebo IV1}_{s,T}$. By averaging across the 1,000 draws, we obtain $\textit{Expected IV}^1_{j,T}$. In the second type of counterfactual shocks, we fix the number of swing states in a given term to be as in Figure 2 and randomize the identity of swing states across the states that were classified as swing at least once during our sample period. Again, we perform 1,000 randomizations, each generating $\textit{Placebo Swing State}^2_{s,T}$, which we use to construct $\textit{Placebo IV}^2_{s,T}$ and $\textit{Expected IV}^2_{j,T}$.

Table 7 reports the results in which we use $\textit{Expected IV}^1_{j,T}$ and $\textit{Expected IV}^2_{j,T}$ (and the corresponding downstream and upstream variables) to recenter the instruments. Tables 7 shows that our 2SLS results on the employment effects of trade protection are robust to addressing concerns about OVB: the sign and magnitude of the coefficients are unaffected when we recenter the instruments using the first type of counterfactual shocks (top panel) or the second (bottom panel).

Table 7

Effects of Trade Protection on Employment Along Supply Chains

(Recentered Instruments)

	Counterfactual shocks 1				
	Manufacturing industries	All industries			
		including diagonal		excluding diagonal	
	(1)	(2)	(3)	(4)	(5)
Direct Tariff Exposure$_{j,T}$	3.975**				
	(1.855)				
Downstream Tariff Exposure$_{j,T}$		-3.452**	-2.832*	-3.051*	-2.711*
		(1.629)	(1.437)	(1.621)	(1.492)
Upstream Tariff Exposure$_{j,T}$		4.193**	2.686**	3.171	2.002
		(1.715)	(1.145)	(2.507)	(1.448)
Sector Fixed Effects	Yes	Yes	Yes	Yes	Yes
Term Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,567	1,915	1,915	1,915	1,915
KP F-statistic	24.5	22.3	34.3	16.5	19.4
	Counterfactual shocks 2				
	Manufacturing industries	All industries			
		including diagonal		excluding diagonal	
	(1)	(2)	(3)	(4)	(5)
Direct Tariff Exposure$_{j,T}$	4.395**				
	(2.080)				
Downstream Tariff Exposure$_{j,T}$		-3.491**	-2.813*	-3.029*	-2.663*
		(1.666)	(1.472)	(1.648)	(1.531)
Upstream Tariff Exposure$_{j,T}$		4.788***	2.979**	3.876	2.307
		(1.761)	(1.151)	(2.690)	(1.509)
Sector Fixed Effects	Yes	Yes	Yes	Yes	Yes
Term Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,567	1,915	1,915	1,915	1,915
KP F-statistic	20.6	20.3	32.5	15.0	18.5

The table reports 2SLS estimates of equations (12) and (13). The dependent variable $\Delta L_{j,T}$ is the log change in employment in SIC4 industry j during term T. The tariff variables capture exposure to AD protection, as measured by (1)-(3), instrumented using the corresponding IV variables. In the top (bottom) panel, the instruments are recentered using *Expected* $IV^1_{j,T}$ (*Expected* $IV^2_{j,T}$) and the corresponding downstream and upstream variables. In columns 2 and 3, the downstream and upstream measures include the diagonal of the input output-matrix and respectively account for direct linkages only or also for higher-order linkages; in columns 4 and 5, they exclude the diagonal of the input-output matrix and respectively account for direct linkages only or also for higher-order linkages. The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). The sample covers all first terms during 1989-2016 and includes all manufacturing industries (all industries) in column 1 (columns 2-5). Observations are weighted by 1988 employment. Sector fixed effects are defined at the SIC4 level. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

The results of a series of additional estimations reported in the Appendix confirm the robustness of our results on the employment effects of politically-motivated protection. As mentioned before, GATT/WTO rules allow for three forms of temporary trade barriers (TTBs): AD duties to defend against imports sold at "less than fair value," countervailing duties to protect against subsidized imports, and safeguard tariffs in response to import surges. In our main analysis, we focus on AD duties, the most common trade barrier used by the United States and other WTO members. Table A-10 shows that the results are unaffected if we further include countervailing duties and safeguards. Table A-11 shows that the results continue to hold if we construct the tariff exposure measure using the alternative measure based on the AD dummy variable. Finally, Table A-12 reports the results when we include the presidency of Donald Trump.

7 Conclusion

Article II of the US Constitution provides for the indirect election of the nation's highest office: the president of the United States is chosen by a group of state-appointed "electors" rather than being directly elected by US citizens. This electoral system has been widely criticized for potentially leading to undemocratic outcomes. Indeed, several US presidents have come into office despite earning fewer votes nationally than the loser.

The Electoral College has also been criticized for giving more power to swing states, in which a small difference in votes can shift all electors from one candidate to the other. It is well known that presidential candidates spend more time and money during their campaigns in these battleground states (Strömberg, 2008). This is the first paper to show that the Electoral College system distorts actual policies, giving rise to distributional effects: to get re-elected, incumbent executives implement policies that favor key industries in swing states, at the expense of other industries.

We show that during first terms — when the US president can be re-elected — the level of AD protection granted to an industry depends on its importance in states expected to be swing. In line with the theoretical model of Conconi *et al.* (2017), our empirical findings suggest that the re-election concerns induce US presidents to manipulate trade policy in favor of key industries in swing states. The results are robust to using different protectionist measures, different definitions of swing states, different measures of the importance of industries in these states, and different sample periods. They also continue to hold when we use different methodologies to address possible identification concerns.

We also provide micro-level evidence, which shows that swing-state politics affects ITC votes on AD cases. We find that the probability that individual ITC commissioners vote in favor of the petitioning industry depends on the importance of the industry in states expected to be swing.

We then study the effects of trade protection in industries directly or indirectly (through input-output linkages) exposed to it. To address concerns about the endogeneity of trade policy, we propose a new shift-share instrument for AD duties. Identification relies on changes in the identity of swing states across electoral terms, which generate plausibly exogenous political shocks. Exposure to these shocks varies across industries, depending on their geographic distribution across states and input-output linkages between them and on their historical experience in dealing with the complex AD proceedings.

We find that politically motivated protection generates winners and losers across industries. It fosters employment growth in protected industries, but hinders growth in downstream industries. The effects are sizeable and continue to hold when we address concerns about non-random industry exposure to the political shocks and in a battery of additional robustness checks. Our findings resonate with concerns often heard in the media about the costs of protection along supply chains.[48]

Our analysis provides new arguments in the ongoing debate about reforming the Electoral College system. Our analysis suggests that abolishing this system would lead to a change in the structure of trade protection. In particular, key input industries such as steel, car parts, industrial machinery and plastic products would lose political importance if all votes and jobs mattered equally in US presidential elections.[49] This could result in lower protection of these industries, with important repercussions for the rest of the economy.

Our analysis also contributes to the academic debate about the rationale for allowing flexible protectionist measures such as AD in trade agreements. Some studies emphasize an economic rationale: the ability to protect industries in the face of import surges can act as a

[48]For example, in a joint statement in March 2018, the National Tooling and Machining Association and the Precision Metalforming Association protested that tariffs on steel "will cost manufacturing jobs across the country," emphasizing that 6.5 million workers are employed in steel- and aluminum-using industries in the US, compared to only 80,000 employed in the steel industry. See "Thousands of jobs at risk over tariffs, US manufacturers warn" (*Financial Times*, March 1, 2018).

[49]An illustration of this idea can be found in Table A-4, in which we consider the 15 largest manufacturing industries in terms of total US employment. For each industry, we measure its size in the United States at large (captured by the variable $\textit{US Industry}_j$) and compare it with its size in swing states (captured by the average of $\textit{Swing Industry}_{j,T}$). The table suggests that, if US presidents cared equally about all votes and jobs, some industries would become politically more important and receive more protection. By contrast, others would see their political importance and their protection decrease. Notice that the latter group includes key input industries such as steel, car parts, and plastic products.

"safety valve," allowing countries to sustain trade policy cooperation (Bagwell and Staiger, 1990). Our paper points to political economy motives for flexible protectionist measures (in the spirit of Bagwell and Staiger, 2005): incumbent politicians use these measures to favor particular industries and increase their chances of retaining power.

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Online Appendix

A-1 Product to Industry Concordance

As explained in Section 4, the Temporary Trade Barriers Database (TTBD) contains detailed information on AD duties and other protectionist measures (countervailing duties and safeguards). For US AD cases, it provides detailed information on the products under investigation, with petitions identified at the 10-digit Harmonized Tariff Schedule (HTS) level (or at the 5-digit Tariff Schedule of the United States Annotated for years before 1989).

To match TTBD data to the SIC4 classification, we first harmonize HS codes over time to the HS 1992 nomenclature, using the concordance tables provided by the United Nations Statistics Division.

We then match the HS codes to the SIC classification using the following procedure:[50]

1. Each 10-digit HTS code is first aggregated up to the universal 6-digit Harmonized System (HS6) level. Then, each HS6 code is matched with one or more 4-digit SIC code using the crosswalk provided by Autor *et al.* (2013). Around 99% of the observations are mapped using this correspondence table.[51] In order to map each HS6 product to only one industry, we assign an HS6 code to the industry which accounts for the largest share of that product's US imports. This means that each HS6 product is mapped to only one 4-digit SIC industry. AD cases often target multiple HS6 products and thus may be linked to more than one SIC4 code.

2. The remaining unmatched HS6 products are mapped to a SIC code by aggregating up the information in the crosswalk to the HS4 level. In this case, a product is matched to an industry if its correspondent HS4 family maps to only one SIC4 industry. All the unmatched HS6 products are manually matched to a corresponding SIC4 industry by directly retrieving information about the corresponding AD case from the ITC case descriptions.

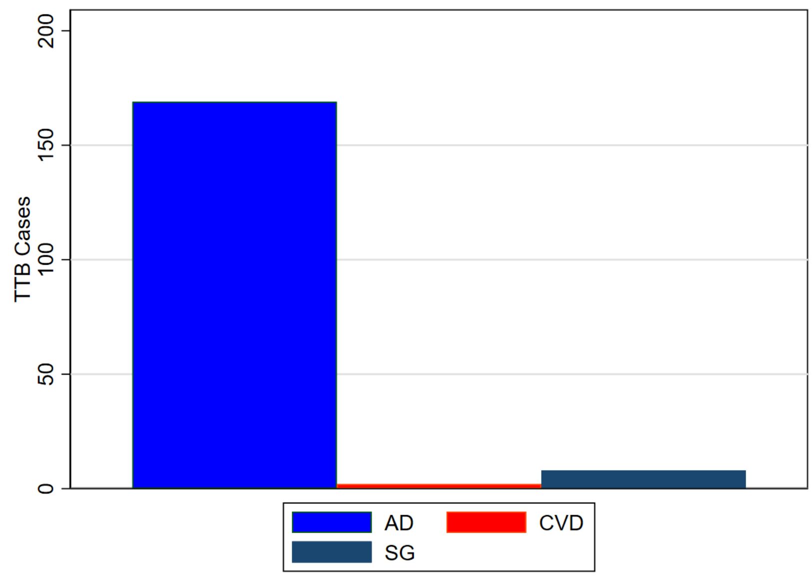
[50] Throughout, when we refer to SIC industries, we use the "sic87dd" scheme used by Autor *et al.* (2013). These codes are slightly coarser than the 1987 SIC codes.

[51] For the years up to 1988, descriptions of products were provided according to the Tariff Schedule of the United States Annotated (TSUSA) classification. Therefore, for AD cases before 1988, we match each TSUSA code with a corresponding HS code using the correspondence table provided by Feenstra (1996).

A-2 Figures

Figure A-1

US Temporary Trade Barriers



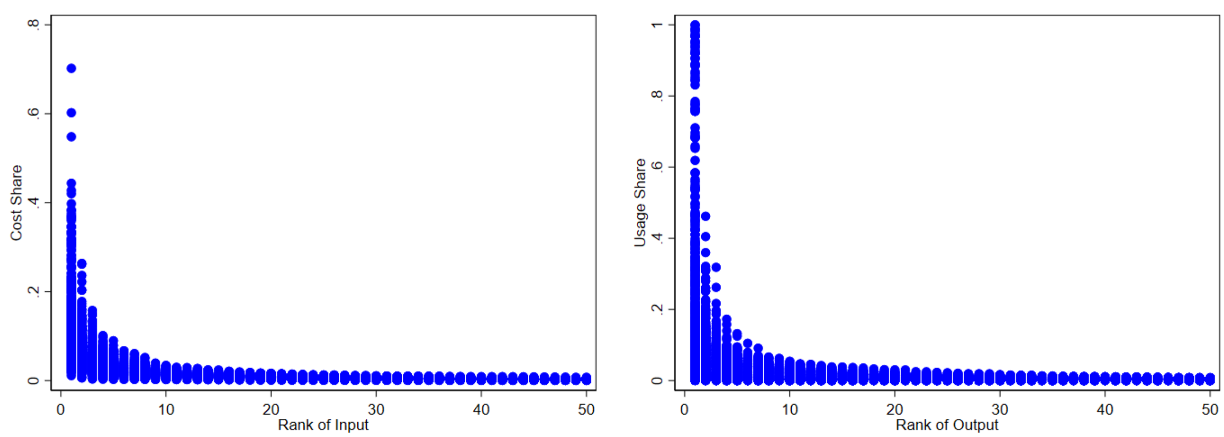
The figure shows the number of US AD duties, countervailing duties (CVDs) and safeguards in force against China during 1989-2020. CVDs bundled with AD duties are counted in the first bar.

Figure A-2

Distribution of IO coefficients

(a) Top-50 input industries

(b) Top-50 output industries

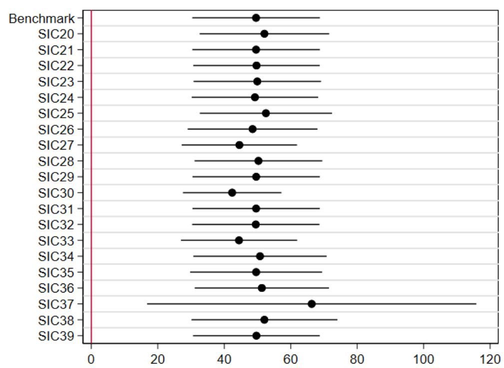


The figures plot cost and usage shares for the 479 SIC4 industries (top-50 input and output industries).

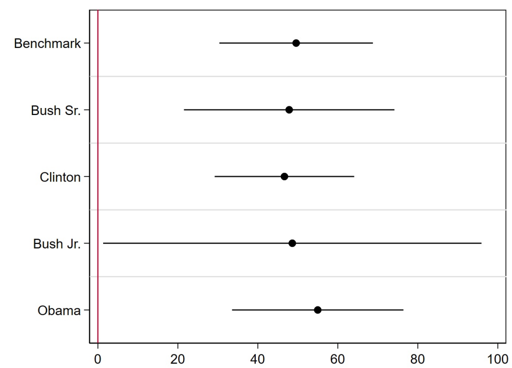
Figure A-3

Swing-State Politics and AD Protection

(a) Dropping Each SIC2 Industry



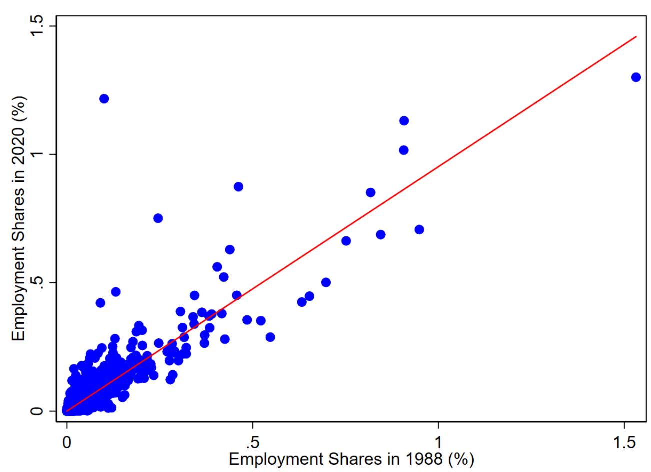
(b) Dropping Each Term



The figures plot the OLS estimates of equation (5) in the baseline specification in column 1 of Table 1, when dropping each SIC2 industry (panel (a)) and each term (panel (b)) from the sample.

Figure A-4

SIC4 employment shares by state



The figure plots state-level industry employment shares in 1988 and 2020, based on CBP data.

A-3 Descriptive Statistics

Table A-1

Top 10 input industries

SIC4	Input industry	Number of output industries (1)	Average cost share (2)
3312	Blast furnaces and steel mills	84	10.6%
2911	Petroleum refining	43	5.0%
2752	Commercial printing, lithographic	31	3.3%
2221	Broadwoven fabric mills, manmade	30	10.1%
2869	Industrial organic chemicals, n.e.c.	26	9.2%
2621	Paper mills	25	19.9%
3679	Electronic components, n.e.c.	23	6.0%
3089	Plastics products, n.e.c.	15	3.8%
2421	Sawmills and planing mills, general	12	1.9%
2821	Plastics materials and resins	12	12.0%

The table lists the 10 most important tradable input industries i by total cost shares. Column 1 reports the number of industries j for which input i is the key input (i.e., highest cost share $\omega_{i,j}$). Column 2 reports the average cost shares of industry i (across all industries j for which i is the key input).

Table A-2

Descriptive statistics of main variables

Variable	Obs.	Mean	Std. dev.	Min	Max
$Direct\ Tariff\ Exposure_{j,t}$	3,136	2.153%	8.520%	0.000%	100.000%
$Downstream\ Tariff\ Exposure^1_{j,t}$	3,832	1.126%	1.596%	0.000%	25.881%
$Upstream\ Tariff\ Exposure^1_{j,t}$	3,832	0.701%	1.732%	0.000%	30.878%
$Downstream\ Tariff\ Exposure^2_{j,t}$	3,832	1.870%	2.195%	0.019%	35.339%
$Upstream\ Tariff\ Exposure^2_{j,t}$	3,832	1.185%	2.647%	0.000%	47.062%
$Downstream\ Tariff\ Exposure^3_{j,t}$	3,832	1.069%	1.529%	0.000%	25.881%
$Upstream\ Tariff\ Exposure^3_{j,t}$	3,832	0.644%	1.654%	0.000%	30.878%
$Downstream\ Tariff\ Exposure^4_{j,t}$	3,832	1.805%	2.124%	0.019%	35.339%
$Upstream\ Tariff\ Exposure^4_{j,t}$	3,832	1.121%	2.561%	0.000%	47.062%
$Swing\ Industry_{j,T}$	3,136	0.058%	0.103%	0.000%	1.345%
$AD\ Experience_j$	3,136	1.235	3.648	0.000	64.000
$IV_{j,T}$	3,136	0.173%	1.498%	0.000%	41.569%

The table reports descriptive statistics of the main variables used in our analysis, which are defined in Section 4. $Direct\ Tariff\ Exposure_{j,t}$ is constructed for all manufacturing industries. $Downstream\ Tariff\ Exposure_{j,t}$ and $Upstream\ Tariff\ Exposure_{j,t}$ are constructed for all industries; the first two versions of these variables include the diagonal of the input-output matrix and are constructed using only direct linkages (version 1) or also higher-order linkages (version 2); the last two versions exclude the diagonal of the input-output matrix and are constructed using only direct linkages (version 3) or also higher-order linkages (version 4). The sample covers the period 1989-2020.

Table A-3

Top-10 Sectors by *Swing Industry*$_{j,T}$ and *AD Experience*$_j$

Sector	Description	Average *Swing Industry*$_{j,T}$	Average *Direct Tariff Exposure*$_{j,T}$
2752	Commercial printing, lithographic	0.77%	2.71%
3714	Motor vehicle parts and accessories	0.75%	3.85%
3089	Plastics products, n.e.c.	0.72%	2.01%
2711	Newspapers	0.51%	0.00%
3711	Motor vehicles and car bodies	0.51%	0.00%
3499	Fabricated metal products, n.e.c.	0.43%	6.41%
3812	Search and navigation equipment	0.39%	0.00%
3312	Blast furnaces and steel mills	0.38%	11.95%
2599	Furniture and fixtures, n.e.c.	0.36%	11.65%
3599	Industrial machinery, n.e.c.	0.34%	4.17%

AD Experience$_j$

Sector	Description	*AD Experience*$_j$	Average *Direct Tariff Exposure*$_{j,T}$
3312	Blast furnaces and steel mills	64	11.95%
2819	Industrial inorganic chemicals, n.e.c.	13	4.31%
3714	Motor vehicle parts and accessories	12	3.85%
2869	Industrial organic chemicals, n.e.c.	10	18.93%
3999	Manufacturing industries, n.e.c.	8	3.28%
3991	Brooms and brushes	7	13.28%
3494	Valves and pipe fittings, n.e.c.	7	10.94%
3496	Misc. fabricated wire products	7	4.69%
2821	Plastics materials and resins	7	3.29%
2399	Fabricated textile products, n.e.c.	7	2.86%

The table lists the top-10 SIC4 sectors with the highest average value of the variable *Swing Industry*$_{j,T}$ during 1989-2020 (top panel) and the highest value of *AD Experience*$_j$ in 1980-1988 (bottom panel), with the corresponding average AD protection.

Table A-4

Largest Manufacturing Industries

Industries with *Swing Industry*$_j$ > *US Industry*$_j$	
3714	Motor vehicle parts and accessories
3312	Blast furnaces and steel mills
3499	Fabricated metal products, n.e.c.
3599	Industrial machinery, n.e.c.
3089	Plastics products, n.e.c.
3711	Motor vehicles and car bodies
2752	Commercial printing, lithographic
2051	Bread, cake, and related products
Industries with *Swing Industry*$_j$ < *US Industry*$_j$	
3721	Aircraft
3728	Aircraft parts and equipment, n.e.c.
2621	Paper mills
2011	Meat packing plants
2711	Newspapers
3812	Search and navigation equipment
2599	Furniture and fixtures, n.e.c.

The table lists the largest 15 manufacturing industries in the United States, based the variable $US\ Industry_j = \frac{\sum_s L_{s,j}}{\sum_s \sum_j L_{s,j}}$, where $L_{s,j}$ is employment in industry j in state s in 1988. The top (bottom) panel includes the industries for which *US Industry*$_j$ is higher (lower) than *Swing Industry*$_j$. This is the average between 1989 and 2020 of the variable $Swing\ Industry_{j,T} = \frac{\sum_s L_{s,j} \times Swing\ State_{s,T} \times EV_s}{\sum_s \sum_j L_{s,j} \times Swing\ State_{s,T} \times EV_s}$.

A-3 The Identity of Swing States and State-Level Characteristics

Our identification strategy relies on exogenous political shocks, driven by changes in the identity of swing states across electoral terms. One may be concerned that the variable $Swing\ State_{s,T}$ could be correlated with state-level characteristics, e.g., the extent to industries in that state have been protected or have been exposed to import competition, or the degree to which employment has been declining. In what follows, we show that these characteristics do not predict which states are classified as swing during a term — i.e., in which states Democratic and Republican candidates get between 47.5% and 52.5% of the share of votes in the midterm House races. To this purpose, we estimate:

$$Swing\ State_{s,T} \times EV_s = \beta_0 + \beta_1 X_{s,T} + \delta_s + \delta_T + \varepsilon_{s,T}. \quad (14)$$

Recall that $Swing\ State_{s,T}$ is a dummy variable identifying battleground states based on the outcome of the House elections during term T, while EV_s is the number of electoral votes assigned to state s at the start of our sample period. $X_{s,T}$ captures state-level variables that may be correlated with the identity of swing states. These variables are constructed by combining the corresponding industry-level variables with industry-state employment shares, i.e., $X_{s,T}$ is equal to $\sum_j \phi_{j,s} X_{j,T}$, where $\phi_{s,j}$ is the 1988 share of employment in manufacturing industry j in state s over total employment in that state. We construct these variables using data on the four years before the midterm elections used to define the identity of swing states in term T. The state fixed effects (δ_s) account for time-invariant state characteristics, while term fixed effects (δ_T) account for changing macroeconomic conditions.

Table A-5 reports the results of estimating (14) with different $X_{s,T}$. In line with the theoretical model of Conconi *et al.* (2017) and the empirical results presented in Section 5.1, we focus on first terms, during which swing-state politics shapes US AD protection.[52] In columns 1 and 2, we verify that the identity of swing states is uncorrelated with state-level trade protection, captured by the variable $Trade\ Protection_{s,T}$. The first (second) version of this variable is based on the share of products in an industry that are subject to AD duties (whether products within an industry are subject to AD duties). The coefficient of this variable is insignificant, indicating that whether a state is classified as swing is independent

[52]The sample used in these regressions starts in 1993. This allows us to have the same number of observations across specifications: data on trade flows start in 1991, so we cannot construct $Import\ Exposure_{s,T}$ for the 1989-1992 term (this would require having trade data from the 1986 midterm elections). The results of Table A-5 are unaffected if we include this term when constructing the other state-level variables: in this case, the number of observations in columns 1-2 and 5-6 increases to 250, but the coefficients of $Trade\ Protection_{s,T}$ and $Employment\ Growth_{s,T}$ remain insignificant.

of the extent to which its industries have been previously protected. This finding addresses concerns that the results of Table 1 may be driven by reverse causality. This, of course, does not imply that protectionist measures have no effects on vote outcomes. What is crucial for our identification strategy is that the extent to which a state has been protected during an electoral term does not affect whether the state is going to be swing at the end of the term, i.e., whether the difference in vote shares between the Democratic and Republican candidates in the midterm House elections falls below the 5% threshold.

Table A-5

Identity of Swing States and State-Level Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
$\textit{Trade Protection}_{s,T}$	231.620	63.554				
	(230.645)	(69.790)				
$\textit{Import Exposure}_{s,T}$			-0.040	7.323		
			(17.375)	(12.883)		
$\textit{Employment Growth}_{s,T}$					-0.016	-0.026
					(0.126)	(0.146)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.46	0.30	0.45	0.45	0.45	0.45
Observations	200	200	200	200	200	200

The table reports OLS estimates of equation (14). The dependent variable is $\textit{Swing State}_{s,T}$ (a dummy variable equal to 1 if state s is classified as swing based on the mid-term House elections during term T) multiplied by EV_s (the number of electoral votes allocated to state s before the start of our sample period). All state-level controls are constructed combining the corresponding industry-level variables with industry-state employment shares. $\textit{Trade Protection}_{s,T}$ measures state-level trade protection during term T. In column 1 (2), this variable is based on the share of products in an industry that are subject to AD duties (whether products within an industry are subject to AD duties). $\textit{Import Exposure}_{s,T}$ captures state-level exposure to import competition during term T. In column 3 (4), this variable is constructed using US trade data with China only (all countries). $\textit{Employment Growth}_{s,T}$ measures the growth rate of employment in state s during term T. In column 5 (6), this variable is constructed using data on manufacturing industries (all industries). The sample covers all executive first terms during 1993-2020. Standard errors in parentheses are clustered at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

In columns 3 and 4, we test whether the identity of swing states is associated with state-level exposure to imports, captured by the variable $\textit{Import Exposure}_{s,T}$. This test is important, as previous studies show that import competition from China affected US electoral outcomes (Autor *et al.*, 2020; Che *et al.*, 2022). We construct two versions of the import exposure variable: the first (second) version is constructed using US trade data with China only (all countries). The estimates show that the identity of swing states does not depend on previous exposure to import competition.

Finally, some studies suggest that trade protection favors declining industries (e.g., Brainard and Verdier, 1997). We thus check if the identity of swing states is associated with employment growth. We construct two versions of the variable $\textit{Employment Growth}_{s,T}$: the first (second) is based on state-level employment is manufacturing industries (all industries). The results reported in columns 5 and 6 show that the extent to which employment has been declining in a state is uncorrelated with whether the vote margin in that state falls below the 5% threshold.

A-4 Additional Results and Robustness Checks

Table A-6

Swing-State Politics and AD Protection

(Second Terms)

	Baseline (1)	All TTBs (2)	AD dummy (3)	Pres. elections (4)	Manuf. industries (5)
$\textit{Swing Industry}_{j,T}$	1.772	1.507	-7.075	6.801	0.125
	(7.715)	(7.700)	(31.567)	(13.907)	(1.548)
Sector FE	Yes	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.49	0.49	0.56	0.49	0.49
Observations	1,176	1,176	1,176	1,176	1,176

The table reports OLS estimates of equation (5). In columns 1, 4, and 5, the dependent variable is $\textit{Trade Protection}_{j,T}$, the share of HS6 products within SIC4 industry j that are subject by AD duties during term T; in column 2, it is the share of products subject to any temporary trade barrier (AD duties, countervailing duties, or safeguards); in column 3, it is a dummy variable equal to 1 if any product in industry j is subject to AD duties. The variable $\textit{Swing Industry}_{j,T}$ is defined in equation (4). In columns 1-4, the denominator of this variable includes all industries; in column 5, it includes only manufacturing industries. In columns 1-3 and 5 (column 4), swing states are identified using data on the outcome of congressional (presidential) in the middle (at the end) of term T. The sample covers all executive second terms during 1989-2020. Observations are weighted by 1988 employment. Sector fixed effects are defined at the SIC4 level. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-7

IV and AD Protection
(Controlling for Swing Industry)

	Baseline	All TTBs	AD dummy	Pres. elections	Manuf. industries	Excluding Trump
	(1)	(2)	(3)	(4)	(5)	(6)
$IV_{j,T}$	0.387***	0.440***	2.147***	0.346***	0.082***	0.302***
	(0.074)	(0.087)	(0.259)	(0.034)	(0.016)	(0.064)
Swing Industry$_{j,T}$	0.802	0.330	26.151***	-0.246	0.289	1.210
	(1.454)	(1.788)	(9.344)	(1.160)	(0.326)	(1.444)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.50	0.50	0.56	0.50	0.56	0.51
Observations	1,960	1,960	1,960	1,960	1,960	1,568

The table reports OLS estimates of equation (5). In columns 1, 4, 5 and 6, the dependent variable is *Trade Protection*$_{j,T}$, the share of HS6 products within SIC4 industry j that are subject by AD duties during term T; in column 2, it is the share of products subject to any temporary trade barrier (AD duties, countervailing duties, or safeguards); in column 3, it is a dummy variable equal to 1 if any product in industry j is subject to AD duties. The variable $IV_{j,T}$ is defined in equation (10). In columns 1-4 and 6, the denominator of the variable *Swing Industry*$_{j,T}$ used to construct $IV_{j,T}$ includes all industries; in column 5, it includes only manufacturing industries. In columns 1-3 and 5-6 (column 4), swing states are identified using data on the outcome of congressional (presidential) in the middle (at the end) of term T. In columns 1-5 (column 6), the sample covers all executive first terms during 1989-2020 (1989-2016). Observations are weighted by 1988 employment. Sector fixed effects are defined at the SIC4 level. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-8

Trade Protection and Employment Along Supply Chains
(OLS Estimates)

	Manufacturing industries	All industries			
		including diagonal		excluding diagonal	
	(1)	(2)	(3)	(4)	(5)
Direct Tariff Exposure$_{j,T}$	-0.067				
	(0.095)				
Downstream Tariff Exposure$_{j,T}$		-2.379**	-1.803*	-2.580**	-1.963*
		(1.087)	(0.990)	(1.175)	(1.042)
Upstream Tariff Exposure$_{j,T}$		0.903	0.575	0.686	0.425
		(0.702)	(0.627)	(0.651)	(0.599)
Sector Fixed Effects	Yes	Yes	Yes	Yes	Yes
Term Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,567	1,915	1,915	1,915	1,915
Adjusted R^2	0.36	0.50	0.50	0.50	0.50

The table reports OLS estimates of equations (12) and (13). The dependent variable $\Delta L_{j,T}$ is the log change in employment in SIC4 industry j during term T. The tariff variables capture exposure to AD protection, as measured by (1)-(3). In columns 2 and 3, the downstream and upstream measures include the diagonal of the input output-matrix and respectively account for direct linkages only or also for higher-order linkages; in columns 4 and 5, they exclude the diagonal of the input-output matrix and respectively account for direct linkages only or also for higher-order linkages. The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). In columns 1 (2-3), the sample includes all manufacturing industries (all industries) and covers all first terms during 1989-2016. Observations are weighted by 1988 employment. Sector fixed effects are defined at the SIC4 level. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-9

Reduced-Form Results for Table 6

	Manufacturing industries	All industries			
		including diagonal		excluding diagonal	
	(1)	(2)	(3)	(4)	(5)
$IV_{j,T}$	1.272***				
	(0.401)				
Downstream $IV_{j,T}$		-1.476	-1.804*	-1.548	-1.810*
		(0.998)	(1.039)	(0.990)	(1.044)
Upstream $IV_{j,T}$		3.541**	3.251**	2.063	2.137
		(1.544)	(1.416)	(1.571)	(1.483)
Sector Fixed Effects	Yes	Yes	Yes	Yes	Yes
Term Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,567	1,915	1,915	1,915	1,915
Adjusted R^2	0.38	0.50	0.50	0.50	0.50

The table reports the reduced-form results of the 2SLS estimates of Table 6. The dependent variable $\Delta L_{j,T}$ is the log change in employment in SIC4 industry j during term T. The tariff variables capture exposure to AD protection, as measured by (1)-(3). In columns 2 and 3, the downstream and upstream measures include the diagonal of the input output-matrix and respectively account for direct linkages only or also for higher-order linkages; in columns 4 and 5, they exclude the diagonal of the input-output matrix and respectively account for direct linkages only or also for higher-order linkages. The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). In columns 1 (2-3), the sample includes all manufacturing industries (all industries) and covers all first terms during 1989-2016. Observations are weighted by 1988 employment. Sector fixed effects are defined at the SIC4 level. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-10

Effects of Trade Protection on Employment Along Supply Chains
(All TTBs)

	Manufacturing industries	All industries			
		including diagonal		excluding diagonal	
	(1)	(2)	(3)	(4)	(5)
Direct Tariff Exposure$_{j,T}$	3.399**				
	(1.614)				
Downstream Tariff Exposure$_{j,T}$		-3.036**	-2.836**	-2.748*	-2.767*
		(1.486)	(1.398)	(1.466)	(1.457)
Upstream Tariff Exposure$_{j,T}$		3.723**	2.389**	2.758	1.682
		(1.544)	(1.079)	(2.117)	(1.319)
Sector Fixed Effects	Yes	Yes	Yes	Yes	Yes
Term Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,567	1,915	1,915	1,915	1,915
KP F-statistic	22.0	38.3	51.7	22.8	37.1

The table reports 2SLS estimates of equations (12) and (13). The dependent variable $\Delta L_{j,T}$ is the log change in employment in SIC4 industry j during term T. The tariff variables capture exposure to all temporary trade barriers (AD duties, countervailing duties, and safeguards), as measured by (1)-(3), instrumented using the corresponding IV variables. In columns 2 and 3, the downstream and upstream measures include the diagonal of the input output-matrix and respectively account for direct linkages only or also for higher-order linkages; in columns 4 and 5, they exclude the diagonal of the input-output matrix and respectively account for direct linkages only or also for higher-order linkages. The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). The sample covers all first terms during 1989-2016 and includes all manufacturing industries (all industries) in column 1 (columns 2-5). Observations are weighted by 1988 employment. Sector fixed effects are defined at the SIC4 level. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-11

Effects of Trade Protection on Employment Along Supply Chains
(Alternative AD Measure)

	Manufacturing industries	All industries			
		including diagonal		excluding diagonal	
	(1)	(2)	(3)	(4)	(5)
Direct Tariff Exposure$_{j,T}$	4.213**				
	(1.963)				
Downstream Tariff Exposure$_{j,T}$		-0.727**	-0.578**	-0.659**	-0.570**
		(0.297)	(0.259)	(0.309)	(0.273)
Upstream Tariff Exposure$_{j,T}$		0.607**	0.373**	0.379	0.246
		(0.274)	(0.175)	(0.295)	(0.187)
Sector Fixed Effects	Yes	Yes	Yes	Yes	Yes
Term Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,567	1,915	1,915	1,915	1,915
KP F-statistic	22.4	54.4	25.9	33.2	27.4

The table reports 2SLS estimates of equations (12) and (13). The dependent variable $\Delta L_{j,T}$ is the log change in employment in SIC4 industry j during term T. The tariff variables capture exposure to all temporary trade barriers (based on whether or not products in an industry are subject to AD duties), as measured by (1)-(3), instrumented using the corresponding IV variables. In columns 2 and 3, the downstream and upstream measures include the diagonal of the input output-matrix and respectively account for direct linkages only or also for higher-order linkages; in columns 4 and 5, they exclude the diagonal of the input-output matrix and respectively account for direct linkages only or also for higher-order linkages. The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). The sample covers all first terms during 1989-2016 and includes all manufacturing industries (all industries) in column 1 (columns 2-5). Observations are weighted by 1988 employment. Sector fixed effects are defined at the SIC4 level. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-12

Effects of Trade Protection on Employment Along Supply Chains
(Including Trump)

	Manufacturing industries	All industries			
		including diagonal		excluding diagonal	
	(1)	(2)	(3)	(4)	(5)
Direct Tariff Exposure$_{j,T}$	3.048**				
	(1.389)				
Downstream Tariff Exposure$_{j,T}$		-1.247*	-1.323*	-1.261*	-1.553*
		(0.681)	(0.780)	(0.695)	(0.847)
Upstream Tariff Exposure$_{j,T}$		2.637**	1.835*	1.366	0.988
		(1.295)	(1.017)	(1.987)	(1.354)
Sector Fixed Effects	Yes	Yes	Yes	Yes	Yes
Term Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,958	2,393	2,393	2,393	2,393
KP F-statistic	27.5	26.7	43.9	24.3	24.0

The table reports 2SLS estimates of equations (12) and (13). The dependent variable $\Delta L_{j,T}$ is the log change in employment in SIC4 industry j during term T. The tariff variables capture exposure to all temporary trade barriers (based on whether or not products in an industry are subject to AD duties), as measured by (1)-(3), instrumented using the corresponding IV variables. In columns 2 and 3, the downstream and upstream measures include the diagonal of the input output-matrix and respectively account for direct linkages only or also for higher-order linkages; in columns 4 and 5, they exclude the diagonal of the input-output matrix and respectively account for direct linkages only or also for higher-order linkages. The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). The sample covers all first terms during 1989-2020 and includes all manufacturing industries (all industries) in column 1 (columns 2-5). Observations are weighted by 1988 employment. Sector fixed effects are defined at the SIC4 level. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

A-4 Effects of Trade Protection on Imports

To examine the employment effects of politically motivated trade protection on imports of products targeted by AD, we estimate the following regression by 2SLS on executive first terms:

$$\Delta Imports_{j,T} = \beta_0 + \beta_1 Direct\ Tariff\ Exposure_{j,T} + \beta_2 Swing\ Industry_{j,T} + \delta_j + \delta_T + \varepsilon_{j,T}, \quad (15)$$

where $\Delta Imports_{j,T}$ is the growth rate of US imports from China in SIC4 industry j during term T. In all specifications, we include SIC4 sector and term fixed effects (δ_j and δ_T). Since the dependent variable is expressed in differences, the sector fixed effects allow us to control for (linear) sectoral trends (e.g., the extent to which an industry is declining or being automated). The tariff exposure variable is defined in equation (1), and it is instrumented by $IV_{j,T}$, which is defined as the interaction between *Swing Industry*$_{j,T}$ and *AD experience*$_j$ (see equation (10)). To account for the effects of other policies that may be used to favor important industries in swing states (e.g., federal subsidies), we include the variable *Swing Industry*$_{j,T}$ not interacted with AD experience. If AD protection is effective in reducing imports from China, the estimated β_1 coefficient should be negative and significant.

The results of estimating (15) are reported in column 1 of Table A-13. The baseline specification of column 1 excludes observations corresponding to sectors with with zero US imports from China. The coefficient of *Direct Tariff Exposure*$_{j,T}$ is negative and significant at the 1% level, and indicates that a one standard deviation increase in predicted trade protection leads to a 43 percentage point decrease in the growth rate of imports. Column 2 shows that the results are robust to including sectors with zero imports at the start or at the end of a term.[53]

Several studies have shown that AD duties targeting one country can lead to an increase in imports from non-targeted countries (e.g., Prusa, 1997; Konings *et al.*, 2001). In columns 3 and 4 of Table A-13, we examine whether AD protection against China led not only to a decrease in imports from China (trade destruction), but also to an increase in US imports from non-targeted countries (trade diversion). To this purpose, we re-estimate (15) but replace the dependent variable with the growth rate of US imports from the rest of the world. In column 3 (4), this variable excludes (includes) zeros. We find no evidence of trade diversion: the coefficient of *Direct Tariff Exposure*$_{j,T}$ is not significant.

[53] In this specification, the dependent variable is $\Delta Imports_{j,T}$, constructed as $\ln(1 + Imports_{j,t}) - \ln(1 + Imports_{j,t-4})$.

Overall, the results of Table A-13 show that AD duties against China driven by swing-state politics lead to a decrease in imports of the targeted products, without significant effects on imports from other countries.

Table A-13

Effects of Trade Protection on Imports

	China		Rest of the World	
	(1)	(2)	(3)	(4)
Direct Tariff Exposure$_{j,T}$	-28.990***	-26.073***	-8.671	-8.623
	(9.173)	(8.491)	(9.869)	(9.848)
SIC4 FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes
Observations	1,480	1,568	1,561	1,568
KP F-statistic	23.1	22.4	22.3	22.4

The table reports 2SLS estimates of equation (15). In columns 1-2 (3-4), the dependent variable is the log change in US imports from China (from non-targeted countries) in SIC4 industry j during term T. Columns 1 and 3 (2 and 4) exclude (include) observations corresponding to zero imports. Observations are weighted by 1988 employment. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.