Politically Motivated Trade Protection*

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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 or even abolish it. This paper shows that this system distorts US trade policies in favor of key industries in swing states, at the expense of other industries. We focus on antidumping (AD) duties, the most widely used protectionist barrier. We first show that, during executive first terms, when the president can be re-elected, the level of AD protection granted to an industry depends on its importance in swing states. We then exploit exogenous variation in the identity of swing states across electoral terms to construct an instrument for AD duties and study their effects along supply chains. We find that politically motivated trade protection fosters growth in key input industries by decreasing imports and increasing prices, but hampers growth in downstream industries by raising production costs.

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1 Introduction

The president of the United States, one of the world's most powerful political leaders, is not directly elected by popular vote. Instead, Article II of the US Constitution provides for the indirect election of the nation's highest office. Citizens express their preference for a candidate from one party. The party that wins most votes in each 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. 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.[2] 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. Strömberg (2008) documents this bias in presidential candidates' campaign visits. Much less is known about whether swing-state politics affects actual policy choices.

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, but are detrimental to other industries. 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 to gain votes in Ohio and Pennsylvania, which were expected to be swing states 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,

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

[2] See, for example, "Does the Electoral College need to be reformed?" *Chicago News*, November 2, 2020.

[3] See "Bush policies follow politics of states needed in 2004" (*USA Today*, June 16, 2002). During the same term, President Bush also introduced AD duties on shrimp imports, notwithstanding strong opposition from US restaurateurs and businesses involved in shrimp processing and marketing. It has been argued that "the duties and wholesale price increases could help save jobs in the South, especially in major political battleground states like North Carolina" ("Bush accuses Vietnam and China of dumping shrimp on U.S. market," *New York Times*, July 7, 2004). Debaere (2009) also points out that the duties on shrimps, which reached 201.6% for some products, had been requested by the Southern Shrimp Alliance, which represented Florida and other states expected to be swing in the 2004 presidential elections.

2016). While these measures are designed to defend producers against "unfair" import competition, they are "simply a modern form of protection" (Blonigen and Prusa, 2003). It is well known that AD duties can be manipulated for political purposes (e.g., Finger *et al.*, 1982), since they can be be easily adjusted to shelter some industries from import competition from particular countries. By contrast, Most-Favoured-Nation (MFN) tariffs are less flexible, since they cannot be easily adjusted over time or targeted to particular countries (see Alfaro *et al.*, 2016).[4]

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] Previous studies show that ITC commissioners are also subject to political pressure (e.g., Moore, 1992; Hansen and Prusa, 1997), particularly from the party that appointed them (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." Second, China is by far the biggest target of US AD protection, and duties against China can more easily be manipulated for political purposes due to its non-market economy (NME) status.[7] Consequently, 73% of US AD measures have been against China since its

[4]In robustness checks, we include in our analysis MFN tariffs, safeguards and countervailing duties.

[5]The White House can shape decisions of the DOC 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 WTO allowed other members to treat China as a NME until December 2016. To this day, the United States has refused to grant the status of a market economy to China. This implies that DOC officials can use flexible methods in their AD decisions, using price and cost information from third surrogate countries.

accession to the WTO and AD petitions involving China resulted in much higher duties: during 1988-2016, the average US AD duty against China was 145%, compared to 47% for other target countries.

Our analysis spans the seven presidential terms covering 1988-2016.[8] We show that the level of AD protection granted to an industry depends on its importance in states expected to be swing. 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 system leads US presidents to manipulate trade policy in favor of key industries in swing states.

As pointed out by Trefler (1993), endogeneity poses a key challenge to identify the impact of trade policies. For this reason, we propose a novel instrument for AD duties to study the effects of politically motivated trade protection. Our identification strategy relies on changes in the identity of swing states across presidential elections, which generate exogenous political shocks. In line with this idea, we show that whether a state is classified as swing in a presidential election — i.e., whether the vote margin between the Democratic and Republican candidates in that state falls below the 5% threshold — is uncorrelated to state-level characteristics. Exposure to political shocks varies across industries, depending on their importance across states (captured by initial employment levels). We also exploit variation across industries in their historical experience in the AD process (captured by pre-sample petitions). 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 logic behind our instrument is that AD protection should be skewed in favor of important industries 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.[9]

We show that the instrument is a strong predictor of trade protection during executive first terms, but has no predictive power during second terms, confirming that swing-state politics only affects US AD duties when the president can be re-elected. Placebo tests, in

[8]We exclude the presidency of Donald Trump, who stacked special tariffs on top of AD duties. The special tariffs were introduced under Section 232 of the Trade Expansion Act of 1962 and under Sections Section 201 and 301 of the Trade Act of 1974 (Bown, 2019) and have triggered the ongoing trade war with China. Our sample period also excludes the Covid-19 pandemic.

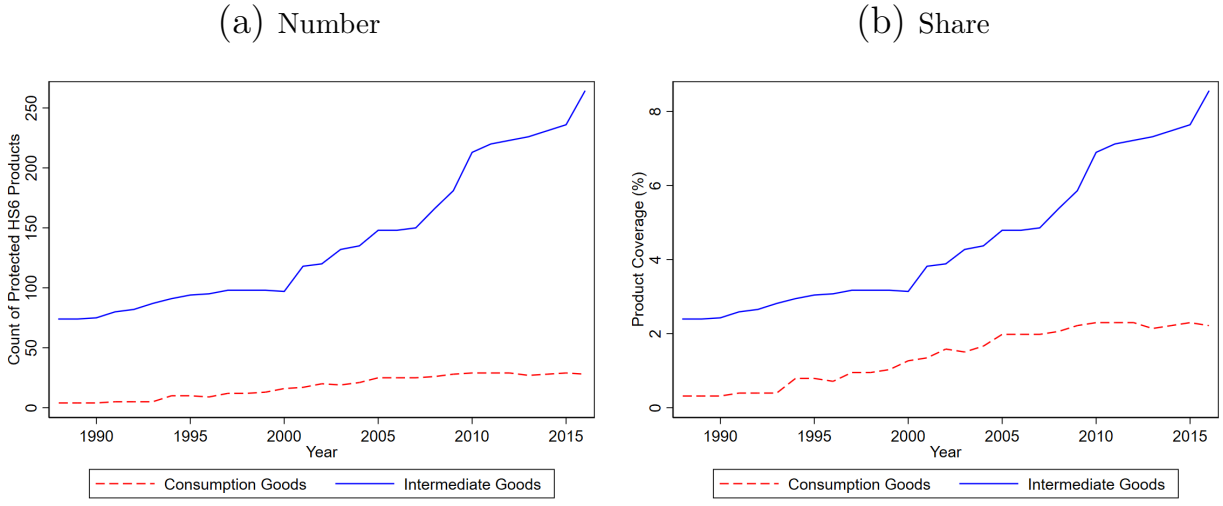
[9]Notice that our instrument is AD specific, since it only predicts trade protection for industries that are important in swing states *and* have prior knowledge of AD proceedings. As discussed in Section 6, this alleviates concerns about the exclusion restrictions.

which we use randomized distributions of swing states to construct our instrument, show that using information on the actual identity of swing states during an electoral term is key for predicting politically motivated protection in that term. We also provide micro-level evidence supporting our identification strategy: the instrument predicts AD votes of ITC commissioners, but only during executive first terms and if the commissioners have been appointed by the party of the incumbent president.

We use the instrument to identify the effects of politically motivated trade protection on industries directly and indirectly exposed to it. 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. This concern is particularly severe for AD duties: unlike MFN tariffs, these measures are skewed towards key input industries (e.g., steel, chemicals, plastics and rubber, car parts). This can be seen in Figure 1, which illustrates the evolution of AD duties on intermediate and final goods during our sample period. When protectionist measures are applied to these intermediate goods (e.g., steel), they can increase production costs for producers in downstream manufacturing (e.g., motor vehicles) and non-manufacturing (e.g., construction) sectors, hampering their growth.

Figure 1

US AD Duties on Intermediate and Consumption Goods



Panel (a) shows the count of HS6 products involving US AD duties against China during 1988-2016. We use the UN BEC classification to distinguish between intermediate and consumption goods. Panel (b) shows the corresponding share over the total number HS6 products in each 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 (0.136) increase in AD protection increases the growth rate of employment in protected industries by 2.5 percentage points, explaining around 12% of the standard deviation of employment growth in those industries. 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 (0.081) increase in input protection decreases the growth rate of employment by 8.5 percentage points, explaining around 39% of the standard deviation of employment growth in downstream industries.

We also provide evidence for the mechanisms behind the employment effects of trade protection. We show that AD duties reduce imports and increase prices in protected industries, raising the input prices faced by producers in downstream industries. These 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 imports of steel and other policies that increase domestic steel prices are harmful to downstream sectors. Barattieri and Cacciatore (2023) estimate the dynamic employment effects of AD duties. They find that these measures have small and insignificant beneficial effects in protected industries. The employment effects in downstream industries are instead negative, sizable, and significant and associated with an increase in input prices.[10]

Our identification strategy relies on exogenous political shocks driven by changes in the identity of swing states across electoral terms. As mentioned before, the identity of swing states is uncorrelated to state-level characteristics (e.g., previous exposure to trade protection and to import competition). 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 the "recentering" methodology proposed by Borusyak and Hull (2023). They also continue to hold in a series of additional robustness checks, e.g., when we include in our analysis all temporary trade barriers (AD duties, safeguards, and countervailing duties) and when we control for US MFN tariffs and foreign retaliatory tariffs.

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 a few key industries in states expected to be swing during an electoral term. These policies

[10]Our findings on the price effects of AD duties are also related to the literature on tariff pass-through. Flaaen *et al.* (2020) find significant price effects due to US import restrictions on washing machines. Several studies examine the price effects of the special tariffs introduced by President Trump against China (e.g., Amiti *et al.*, 2019; Flaaen and Pierce, 2019; Fajgelbaum *et al.*, 2020; Cavallo *et al.*, 2021).

generate winners and losers across industries, in line with arguments often heard in the media. For example, the CEO of the Bicycle Corporation of America complained about tariffs on Chinese imports of bike components, steel and aluminium, which have raised production costs. As a result, the industry's "plans to expand are on hold, costing American jobs."[11] Our results imply that, if US voters directly elected the president, key input industries would receive lower trade protection, with beneficial effects for the rest of the economy.

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 shows that swing-state politics affects US AD duties. Section 6 discusses our instrumental variable strategy. Section 7 presents the 2SLS results on the effects of political motivated trade protection. Section 8 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 towards 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. 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

[11] "The Trouble with Putting Tariffs on Chinese Goods" (*The Economist*, May 16, 2019).

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,[12] 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 (e.g., Gallaway *et al.*, 1999) 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, 1982; Moore, 1992; Hansen and Prusa, 1997; Aquilante, 2018). Ours is the first paper to propose an instrumental variable for these measures and to show that they are shaped by swing-state politics.

Finally, our paper contributes to the literature on trade policy and input-output linkages. 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 competences: the US Department of Commerce (DOC),[13] which is in charge of the dumping

[12]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.

[13]Before 1980, the US Department of Treasury was in charge of dumping investigations. The US Congress decided to move 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).

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 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.[14] 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.[15]

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 third surrogate countries to determine the dumping margin. When focusing on cases targeting China during 1988-2016, the 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 Section 201 of the Trade Act of 1974, 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 1988-2016, the ITC ruled in favor of the petitioning industry in 76% of the cases targeting China. The average AD duty against China was 145%.

[14] 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.

[15] Petitioners must provide the identity of all producers in the industry and their position regarding the petition, as well as detailed description 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 Guidelines for Antidumping Duty Petitions).

After positive rulings by both the DOC and the ITC, AD measures are introduced for a period of five years, after which they are subject to expiry 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 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 seven presidential terms covering 1988-2016, the US initiated 185 cases involving imports from China.

To capture trade protection granted to SIC4 industry j during presidential term T, we define the variable *Trade Protection*$_{j,T}$. In our baseline specification, this is a dummy variable equal to 1 if HS6 products in industry j are subject to AD duties during term T. In robustness checks, we use two alternative definitions: a dummy variable equal to 1 if HS6 products within industry j are subject to AD duties or other TTBs (countervailing duties or safeguards) during term T;[16] and the average share of HS6 products within industry j that are subject to AD duties during term T.[17]

[16]While AD duties are meant to protect domestic producers against imports of "dumped" products, countervailing can be used to protect them against imports of subsidized products.

[17]Recall that AD duties are subject to expiry reviews every five years. Within an industry j, variation in *Trade Protection*$_{j,T}$ across electoral terms thus comes both from the imposition of new measures, and the

As discussed in the introduction, AD duties are known to be shaped by political motives, particularly when they target China. It is thus not surprising that the variable *Trade Protection*$_{j,T}$ is uncorrelated with the extent to which a sector is subject to import competition, captured by the variable $IPO_{j,T}$.[18]

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 use their concordance guide to convert 6-digit BEA industry codes into 4-digit Standard Industry Classification (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-1 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 key role in the US economy. In particular, steel (SIC 3312) is the most important input for 82 industries (see Table A-1). Interestingly, steel is often a key industry in swing states and one of main recipients of AD protection (see Table A-4).

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 simply captured by

$$\textit{Direct Tariff Exposure}_{j,T} = \textit{Trade Protection}_{j,T}, \tag{1}$$

where *Trade Protection*$_{j,T}$ is a dummy variable equal to 1 if HS6 products within industry j are subject to AD duties during term T (or one of the alternative protectionist measures).

Exposure by downstream industries is given by

$$\textit{Downstream Tariff Exposure}_{j,T} = \sum_{i=1}^{N} \omega_{i,j} \, \textit{Trade Protection}_{i,T}, \tag{2}$$

revocation or renewal of old measures.

[18]This is ratio of US imports from China divided by total US expenditures on goods, measured as US gross output plus imports minus US exports. The correlation between $IPO_{j,T}$ and *Trade Protection*$_{j,T}$ is close to zero and insignificant.

[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).

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 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.

In our baseline specifications, we construct the downstream and upstream measures using the Leontief inverse of the input-output matrix to account for higher-order linkages and including the diagonal of the input-output matrix ($\omega_{j,j}$ and $\theta_{j,j}$) to account for within-industry vertical linkages. Table A-2 reports descriptive statistics of the tariff exposure variables.

4.2 Swing States

In line with earlier studies (e.g., Conconi *et al.*, 2017; Ma and McLaren, 2018), we classify swing states based on the difference in the vote shares of Democratic and Republican candidates in presidential elections.[21] In particular, we define the dummy variable $\textit{Swing State}_{s,T}$ to be equal to 1 in state s, if the vote margin between the candidates of the two parties in the presidential elections at the end of term T is below the 5% threshold.

Figure 2 illustrates which states were classified as swing based on this definition in the last 9 presidential elections.[22] Notice that both the number and the identity of swing states varies across elections. In Section 6.4, we will show that using information on the states expected to be swing in a given electoral term is key to predicting AD protection in that term.

The variable $\textit{Swing State}_{s,T}$ captures states that are expected to be swing during term T and is significantly correlated with expectations about the identity of swing states based on presidential polls. This can be seen by looking at polling data on US presidential elections from FiveThirtyEight. The correlation between the expected and realized difference in vote shares of the Democratic and Republican candidates is equal to 0.82 and is significant at the

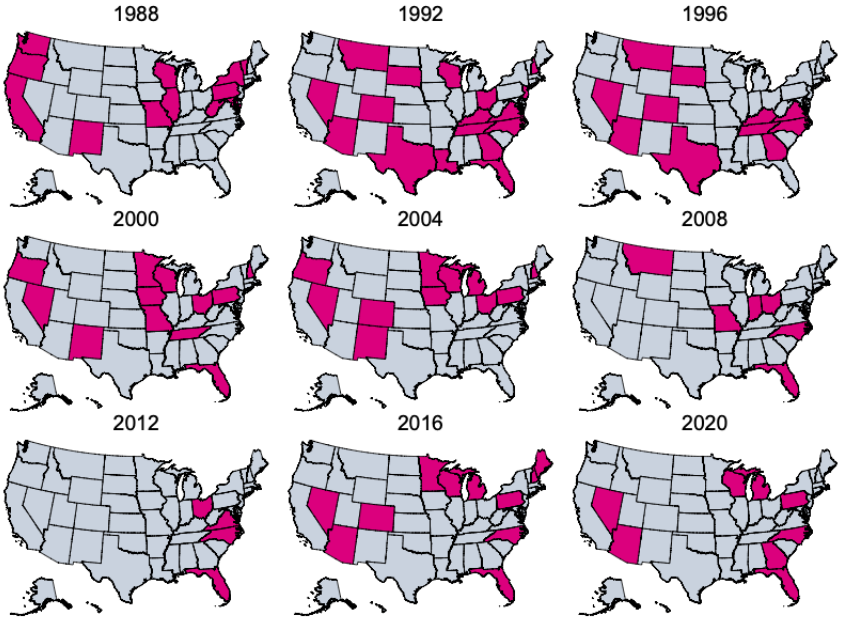
[21] Data on electoral outcomes come from Dave Leip's Atlas of U.S. Presidential Elections.

[22] In our analysis, we focus on the period 1988-2016. We exclude the presidency of Donald Trump, during which AD duties were combined with special tariffs justified under rarely used US trade laws (Sections 201 and 301 of the Trade Act of 1974, Section 232 of the Trade Expansion Act of 1962).

1% level.[23] The correlation between the *Swing State*$_{s,T}$ variables constructed using expected and realized votes is equal to 0.42 and is significant at the 1% level.

Figure 2

Swing states in presidential elections



The states in pink are those classified as swing (i.e., less than 5% difference in the vote shares of Democratic and Republican candidates) in the last nine presidential elections: in 1988, California, Illinois, Maryland, Missouri, New Mexico, New York, Oregon, Pennsylvania, Vermont, Washington, West Virginia, and Wisconsin; in 1992, Arizona, Colorado, Florida, Georgia, Kentucky, Louisiana, Montana, Nevada, New Hampshire, New Jersey, North Carolina, Ohio, South Dakota, Tennessee, Texas, Virginia, and Wisconsin; in 1996, Arizona, Colorado, Georgia, Kentucky, Montana, Nevada, North Carolina, South Dakota, Tennessee, Texas, and Virginia; in 2000, Florida, Iowa, Minnesota, Missouri, Nevada, New Hampshire, New Mexico, Ohio, Oregon, Pennsylvania, Tennessee, and Wisconsin; in 2004, Colorado, Iowa, Michigan, Minnesota, Nevada, New Hampshire, New Mexico, Ohio, Oregon, Pennsylvania, and Wisconsin; in 2008, Florida, Indiana, Missouri, Montana, North Carolina, and Ohio; in 2012, Florida, North Carolina, Ohio, and Virginia; in 2016, Arizona, Colorado, Florida, Maine, Michigan, Minnesota, Nevada, New Hampshire, North Carolina, Pennsylvania, and Wisconsin; in 2020, Arizona, Florida, Georgia, Michigan, Nevada, North Carolina, Pennsylvania, and Wisconsin.

4.3 Importance of Industries in Swing States

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

$$Swing\ Industry_{j,T} = \frac{\sum_s L_{s,j} \times Swing\ State_{s,T} \times EV_s}{\sum_s \sum_j L_{s,j} \times Swing\ State_{s,T} \times EV_s}. \tag{4}$$

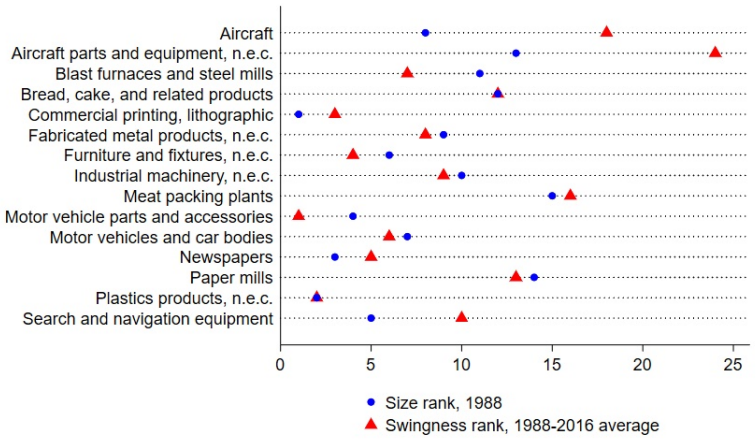
[23]For each presidential election and state, we have used the trend-adjusted average vote shares.

To account for differences in the political importance of swing states, we multiply the dummy variable *Swing State*$_{s,T}$ by EV_s, the number of electoral votes assigned to state s at the start of our sample period (1988).[24] The variable $L_{s,j}$ measures employment of industry j in state s and is also constructed using data from the first year of our sample period.[25] *Swing Industry*$_{j,T}$ is thus the ratio of the 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 *Swing Industry*$_{j,T}$ comes from changes in the identity of swing states across electoral terms (captured by the dummy variable *Swing State*$_{s,T}$). Within a term T, cross-industry variation comes from differences in the importance of industries across states (captured by the initial employment levels $L_{s,j}$). Descriptive statistics of the variable *Swing Industry*$_{j,T}$ are reported in Table A-3. The top panel of Table A-4 lists the top-10 SIC4 sectors with the highest average value of *Swing Industry*$_{j,T}$ during 1988-2016.

Figure 3

Ranking of Industries in Terms of Size and Political Importance in Swing States



The blue dots show the ranking of manufacturing industries in terms of size (based on 1988 employment), focusing on the largest 15 industries. The red triangles indicate the ranking of these industries by their political importance in swing states (based on the average of *Swing Industry*$_{j,T}$ during 1988-2016).

[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 and in the last year of our sample is above 0.95, as shown in Figure A-2).

[26]In our baseline regressions, the denominator of *Swing Industry*$_{j,T}$ is constructed using information on state-level employment in all manufacturing sectors. Outside manufacturing, the industry classification is much more aggregate, which is one of the reasons why most studies of the employment effects of tariffs focus on manufacturing sectors (e.g., Pierce and Schott, 2016; Flaaen and Pierce, 2019). As discussed below, the results are robust to replacing the denominator of (4) with state-level employment in all sectors.

The Electoral College system implies that large industries in swing states are politically more important than their overall size in the United States would suggest. To illustrate this, in Figure 3 we consider the largest 15 manufacturing industries in terms of overall US employment at the start of our sample period (1988). The blue dots show the ranking of industries in terms of total US employment. The red triangles indicate the ranking of the industries in terms of their importance in swing states, based on the average of $Swing\ Industry_{j,T}$ during 1988-2016. Notice that in the case of several key input industries (e.g., blast furnaces and steel mills, motor vehicle parts and accessories), the red triangle is to the left of the blue dot, implying that swing-state politics increases the importance of the industry.

4.4 Historical Experience in AD Proceedings

As mentioned before, the process to petition for AD duties is extremely complex (see also footnote 15): "the petitioning party must present the AD authorities with a reasonable petition that presents their case for the investigation and then provide substantial information, as well as legal analysis and arguments, during the course of the investigation. The legal details, as well as the practical issues of how government agencies apply the law, are substantial" (Blonigen (2006), p. 716). As a result of this complexity, prior experience in petitioning plays an important role in AD filings and outcomes. Blonigen shows that previous experience lowers future filing costs and increases petitioners' effectiveness in arguing their case, generating higher probabilities of favorable outcomes.

Building on these arguments, we construct a variable capturing cross-industry variation in historical (pre-sample) knowledge of AD procedures. This is the count of AD petitions filed by industry j between 1980 and 1987:[27]

$$AD\ Experience_j = \sum_{t=1980}^{1987} AD\ Petitions_{j,t}. \tag{5}$$

Descriptive statistics of the variable $AD\ Experience_j$ are reported in Table A-3. There is significant cross-sectoral variation in the number of AD cases initiated during this period (the variable $AD\ Experience_j$ has a mean close to 1.2 and a standard deviation of around 3.6) possibly due to the fact that 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

[27]During the 1980s, legal and institutional changes in AD proceedings made it easier to file for AD protection, which led to a steep increase in the number of AD petitions (see Irwin, 2005).

Arrangement). The bottom panel of Table A-4 lists the top-10 SIC4 sectors with the highest value of *AD Experience*$_j$ during 1980-1987. The variable *AD Experience*$_j$ is positive for 45% of manufacturing industries.[28]

5 Swing State Politics and Trade Protection

In this section, we show that swing-state politics distorts US trade policy. This finding aligns with the theoretical model proposed by Conconi *et al.* (2017). The model 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. Second, the incumbent's ability to set trade policy provides an advantage over the challenger, who cannot commit to trade policy before being elected. In this setting, the incumbent president has incentives to manipulate trade policy to boost his re-election.[29] During executive first terms — when the incumbent president can be re-elected — AD protection should thus be skewed towards key industries in swing states. To verify this, we restrict the sample to the first terms and estimate:

$$\textit{Trade Protection}_{j,T} = \beta_0 + \beta_1 \textit{Swing Industry}_{j,T} + \delta_j + \delta_T + \varepsilon_{j,T}. \tag{6}$$

where *Swing Industry*$_{j,T}$ captures the importance of SIC4 industry j in states classified as swing during term T (see equation (4)). We include sector fixed effects at the SIC4 level (δ_j) and term fixed effects (δ_T). Industry fixed effects allow us to control for any time-invariant characteristic that may affect the extent to which an industry is protected. The inclusion of term fixed effects accounts for time-varying macroeconomic and political conditions. In line with earlier studies (e.g., Pierce and Schott, 2016), we weight regression estimates by

[28]The highest number of petitions (63) was filed by the steel industry (SIC 3312). Our results continue to hold if we exclude steel from our sample. 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 in 1988-2016 and *AD Experience*$_j$ is 0.88. 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 data, we find no evidence that more experienced industries file weaker cases: the correlation between *AD Experience*$_j$ and the average dumping margin of cases filed by industry j is 0.04 and not statistically significant.

[29]Reciprocal preferences only matter if voters are not too ideological and can thus "swung" by trade policy. 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 directly affect AD decisions of the DOC, which is part of the executive branch (top officials are directly nominated by the president). Several studies show that ITC commissioners are also influenced by political pressure.

start-of-period (1988) industry employment.[30] We cluster standard errors at the SIC3 level (221 industries) to allow for correlated industry shocks.

The results of estimating (6) are reported in Table 1. In column 1, we use our baseline definitions of the variables *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. This result continues to hold in the remaining specifications of Table 1. In columns 2 and 3, we use the alternative definitions of trade protection. In column 4, we modify the definition of the variable *Swing Industry*$_{j,T}$, including in its denominator all employment in all sectors (rather than only in manufacturing sectors). The coefficient of the variable *Swing Industry*$_{j,T}$ remains positive and significant in all specifications. We have verified that this result continues to hold if we drop each SIC4 industry at a time or each term at a time from our sample.[31]

Table 1
Swing-State Politics and AD Protection

	AD dummy	Product share	All TTBs	All industries
	(1)	(2)	(3)	(4)
Swing Industry$_{j,T}$	11.566**	0.682**	11.261**	52.044***
	(0.289)	(0.275)	(1.281)	(0.228)
Sector FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.54	0.50	0.52	0.55
Observations	1,568	1,568	1,568	1,568

The table reports OLS estimates of equation (6). In columns 1 and 4, the dependent variable is *Trade Protection*$_{j,T}$, a dummy variable equal to 1 if products in SIC4 industry j are covered by AD duties during term T; in column 2, it is the average share of products in SIC4 industry j covered by AD duties during term T; in column 3, it is a dummy variable equal to 1 if products in SIC4 industry j are covered by any temporary trade barrier (AD duties, countervailing duty, or safeguards) during term T. In columns 1, 2, and 3, the denominator of the variable *Swing Industry*$_{j,T}$ includes all manufacturing industries; in column 4, it includes all industries. The sample includes manufacturing industries and covers all executive first terms during 1998-2016. 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-5 in the Appendix reports the results of estimating (6) when focusing on executive second terms. The coefficient of the variable *Swing Industry*$_{j,T}$ is never significant.

[30] This accounts for the heterogeneity in the size of SIC4 industries. The results are qualitatively similar if we estimate unweighted linear regressions.

[31] The results of these additional estimations are available upon request.

Comparing Table 1 and Table A-5 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.[32] Swing-state politics has no impact on AD duties during second terms, when the president is a lame duck.

6 Identification Strategy

The main goal of our paper is to study the effects of trade protection driven by swing-state politics. Using ordinary least squares (OLS) would not identify causal effects because of an 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").[33] In our setting, the shifters are political shocks driven by changes in the identity of swing states across electoral

[32]Notice that the number of observations in Table A-5 is lower than in Table 1. This is because one president (Bush senior) was in office for only one term. This is, however, not the reason behind the difference in the results: even if we drop the 1988-1992 term, the coefficient of $Swing\ Industry_{j,T}$ remains positive and significant in first terms.

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

terms; the shares are constructed using information on industries' employment in swing states and their historical experience in AD proceedings.

Our identification strategy relies on the exogeneity of the political shocks.[34] Figure 2 illustrates variation in the identity of swing states across presidential elections. Notice that some states have been swing multiple times. As shown in Section 6.4, our instrument only works if we use information on the identity of swing states in a given electoral term: if we fix the number of times in which a state is swing to be the same as in Figure 2 (e.g., 5 for Ohio and Florida, 3 for Arizona and Missouri, 2 for Kentucky and Iowa, 1 for Maine and Vermont), but randomize across electoral terms, we cannot predict AD protection.

We next provide evidence supporting the assumption of exogenous shocks, showing that the identity of swing states is uncorrelated with various state-level characteristics. To this purpose, we estimate:

$$\textit{Swing State}_{s,T} \times EV_s = \beta_0 + \beta_1 X_{s,T} + \delta_s + \delta_T + \varepsilon_{s,T}. \tag{7}$$

Recall that $\textit{Swing State}_{s,T}$ is a dummy variable equal to 1 in state s if the vote margin between the Democratic and Republican candidates in the presidential elections at the end of term T is less than 5%, 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.[35] The state fixed effects (δ_s) account for time-invariant state characteristics, while term fixed effects (δ_T) account for changing macroeconomic conditions.

Table 2 reports the results for first terms, during which swing-state politics shapes US AD protection, as shown in the previous section (the corresponding results for second terms can be found in Table A-6). In column 1, we verify that the identity of swing states is uncorrelated with state-level trade protection, captured by the variable $\textit{Trade Protection}_{s,T}$. The coefficient of this variable is insignificant, indicating that whether a state is classified as swing is independent of the extent to which its industries have been previously protected. The same is true for state-level changes in trade protection, as shown in column 2. 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

[34] We also take the shares to be exogenous. However, this assumption can be relaxed, allowing for non-random industry exposure to the shocks. In Section 7.1.2 we show that our results are unaffected if we apply the "recentering" methodology proposed by Borusyak and Hull (2023).

[35] These variables are constructed 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 manufacturing industries in that state. The results are robust to defining the shares over total state-level employment.

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 next presidential elections falls below the 5% threshold.

Table 2
Identity of Swing States and State-Level Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Trade Protection$_{s,T}$	25.832					
	(15.641)					
Δ*Trade Protection*$_{s,T}$		-0.171				
		(0.164)				
Import Eposure$_{s,T}$			0.300			
			(8.435)			
Δ*Import Eposure*$_{s,T}$				-0.035		
				(0.231)		
Employment$_{s,T}$					-1.768	
					(2.236)	
Δ*Employment*$_{s,T}$						-0.011
						(0.038)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.49	0.48	0.47	0.47	0.48	0.47
Observations	200	200	200	200	200	200

The table reports OLS estimates of equation (7). *Trade Protection*$_{s,T}$ (Δ*Trade Protection*$_{s,T}$) captures (changes in) state-level trade protection during term T. *Import Exposure*$_{s,T}$ (Δ*Import Exposure*$_{s,T}$) captures (changes in) state-level exposure to import competition during term T. *Employment*$_{s,T}$ (*Employment Growth*$_{s,T}$) measures manufacturing employment (the growth rate of manufacturing employment) in state s during term T. The sample covers all executive first terms during 1988-2016. Standard errors in parentheses are clustered at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

In columns 3 to 6, we test if our swing variable is associated with other state-level characteristics correlated with industry employment. First, we verify that *Swing State*$_{s,T} \times EV_s$ is uncorrelated with the level (*Import Exposure*$_{s,T}$) and the change (Δ*Import Exposure*$_{s,T}$). of state-level exposure to imports.[36] 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). The estimates in columns 3 and 4 show that the identity of swing states does not depend on previous exposure to import competition, expressed in level or changes. It can be argued that the Electoral College provides incentives to favor large states. In column 5, we

[36]The import exposure variables are constructed combining information on US production and US imports from China. Their coefficients remain insignificant if we use information on US overall imports.

show that the identity of swing states does not depend on the size of their manufacturing workforce ($Employment_{s,T}$). Finally, previous 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. The results reported in column 6 show that employment growth rate is uncorrelated with whether the vote margin in that state falls below the 5% threshold.

We next discuss how we measure heterogeneous exposure across industries to the state-level political shocks captured by the variable $Swing\ State_{s,T}$. One option would be to simply use as an instrument the variable $Swing\ Industry_{j,T}$ defined in equation (4). In this case, industries would only differ in their initial employment levels in different states ($L_{s,j}$). However, this strategy would raise concerns about the exclusion restriction. To obtain a consistent estimate of the causal impact of trade protection, the proposed instrument should be uncorrelated with any other determinant of the dependent variable (Angrist and Pischke, 2009). By itself, the variable $Swing\ Industry_{j,T}$ could capture the effects of other policies that may be used to favor key industries in swing states (e.g., federal subsidies), thus violating the exclusion restriction.[37] To address this concern, we define our instrument as the interaction between an industry's (time-varying) importance in swing states, captured by the variable $Swing\ Industry_{j,T}$, and its (time-invariant) historical experience in AD proceedings, captured by the variable $AD\ Experience_j$:

$$IV_{j,T} = Swing\ Industry_{j,T} \times AD\ Experience_j. \tag{8}$$

The instrument is AD specific, since it 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. This alleviates concerns about the exclusion restriction.[38] As discussed below, interacting $Swing\ Industry_{j,T}$ with $AD\ Experience_j$ also improves the predictive power of the instrument. Notice that within-industry variation in predicted AD protection comes only from the exogenous political shocks captured by the dummy variable $Swing\ State_{s,T}$ used to construct $Swing\ Industry_{j,T}$.

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

[37] There is indeed some evidence that swing-state politics affects federal subsidies (Navarra, 2023).

[38] To further address these concerns, in our 2SLS regressions, we will account for the effects of other policies that could be driven by swing-state politics by including as a control the variable $Swing\ Industry_{j,T}$ and the corresponding measures for downstream and upstream industries.

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 the two panels of Table A-4), are among the most protected.

6.2 Predicting Trade Protection

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

$$\textit{Trade Protection}_{j,T} = \beta_0 + \beta_1 IV_{j,T} + \delta_j + \delta_T + \varepsilon_{j,T}. \tag{9}$$

Table 3 shows that the estimated coefficient of $IV_{j,T}$ is always positive and highly significant.[39] Comparing the estimates of Table 3 with the corresponding estimates of Table 1 shows that combining $\textit{Swing Industry}_{j,T}$ with $\textit{AD Experience}_j$ increases the predictive power of our instrument. This finding is in line with Blonigen (2006)'s argument that industries' long-term knowledge of the complex AD proceedings is an important determinant of AD protection.

Table 3
IV and AD Protection

	AD dummy	Product share	All TTBs	All industries
	(1)	(2)	(3)	(4)
$IV_{j,T}$	0.835***	0.069***	0.816***	0.254***
	(0.238)	(0.004)	(0.233)	(0.015)
Sector FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes
Observations	1,568	1,568	1,568	1,568
Adjusted R^2	0.56	0.50	0.54	0.50

The table reports OLS estimates of equation (9). In columns 1 and 4, the dependent variable is $\textit{Trade Protection}_{j,T}$, a dummy variable equal to 1 if products in SIC4 industry j are covered by AD duties during term T; in column 2, it is the average share of products in SIC4 industry j covered by AD duties during term T; in column 3, it is a dummy variable equal to 1 if products in SIC4 industry j are covered by any temporary trade barrier (AD duties, countervailing duty, or safeguards) during term T. In columns 1, 2, and 3, the denominator of the variable $\textit{Swing Industry}_{j,T}$ used to construct $IV_{j,T}$ includes all manufacturing industries; in column 4, it includes all industries. The sample includes manufacturing industries and covers all executive first terms during 1998-2016. 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.

[39] The results continue to hold if we drop each industry and each term at a time from the sample and if we winsorize the experience variable. The results of these additional estimations are available upon request.

Table A-7 in the Appendix shows that the results of Table 3 are unaffected if we further include the variable *Swing Industry*$_{j,T}$ in equation (9). Interestingly, the coefficient of this variable is never significant. This finding indicates that industries that are important in swing states but have no historical experience at petitioning for AD duties do not benefit from trade protection. Indeed, 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-4).

Table A-8 reproduces Table 3 focusing on second terms. The estimated coefficient of the variable $IV_{j,T}$ is never significant. Our instrument is thus a strong predictor of trade protection when the incumbent can be re-elected; it has no predictive power when the president is a lame duck.

6.3 Micro-Level Evidence Supporting our Identification Strategy

As mentioned before, the theoretical model by Conconi *et al.* (2017) implies that a US president in his first term can boost his chances to retain office by protecting key industries in swing states. Moreover, Aquilante (2018) shows that, when voting on AD, ITC commissioners respond to the interests of the political party that appointed them. Based on these studies, we would then expect our instrument to predict AD votes of ITC commissioners, but only i) if they have been appointed by the party of the incumbent president and ii) if the president can be re-elected. To verify this, we consider all final ITC votes on AD cases during 1988-2016 and estimate the following regression separately for executive first and second terms:[40]

$$\begin{aligned} Vote_{i,c(j),t} &= \beta_0 + \beta_1 IV_{j,T} \times \textit{President's Party}_{i,T} + \beta_2 IV_{j,T} + \beta_3 \textit{President's Party}_{i,T} \\ &\quad + \delta_i + \delta_j + \delta_t + \varepsilon_{i,c(j),t}. \end{aligned} \tag{10}$$

$Vote_{i,c(j),t}$ is a dummy variable which is equal to 1 if ITC commissioner i votes in favor of AD duties on case c (involving SIC4 industry j) in year t. *President's Party*$_{i,T}$ is a dummy variable equal to 1 if commissioner i has been appointed by the party of the president who is in office during term T. The key control variable of interest is the interaction between this variable and $IV_{j,T}$. We include fixed effects that capture time-invariant characteristics of ITC commissioners (δ_i), time-invariant characteristics of petitioning industries (δ_j) and broad economic and political conditions at the time of the vote (δ_t).

[40] Consistently with the rest of our analysis, we consider ITC votes on all AD cases in which China is a target country.

The results reported in Table A-9 provide micro-level evidence supporting our instrument: $IV_{j,T}$ predicts ITC votes on AD, but only i) for commissioners who have been appointed by the party of the incumbent president (the β_2 coefficient is never significant) and ii) if the president can be re-elected (the β_1 is positive and significant only in column 1).

6.4 Placebo Tests

As discussed above, our identification strategy exploits variation in the identity of swing states across electoral terms. In what follows, we show that using information on the states expected to be swing in a given electoral term is key to predicting AD protection in that term. To this purpose, we carry out placebo tests, randomizing the identity of swing states used to construct our instrument.

We perform two types of randomizations. In the first, we consider the 26 states that were classified as swing at least once during seven presidential terms covering the period 1988-2016.[41] We fix the number of times in which a state is swing to be the same as in Figure 2 (e.g., 5 for Ohio and Florida, 3 for Arizona and Missouri, 2 for Kentucky and Iowa, 1 for Maine and Vermont), but randomize across electoral 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 *Placebo Swing State1*$_{s,T}$, which we use to construct *Placebo IV1*$_{s,T}$.[42] In the second type of randomization, we keep the number of swing states in a given term to be as in Figure 2 (e.g., 6 states for the presidential term ending in 2008 and 4 states for the presidential term ending in 2012) and randomize across the 26 states that were classified as swing at least once during 1988-2016. Again, we perform 1,000 randomizations, each generating *Placebo Swing State2*$_{s,T}$ and a *Placebo IV2*$_{s,T}$.[43]

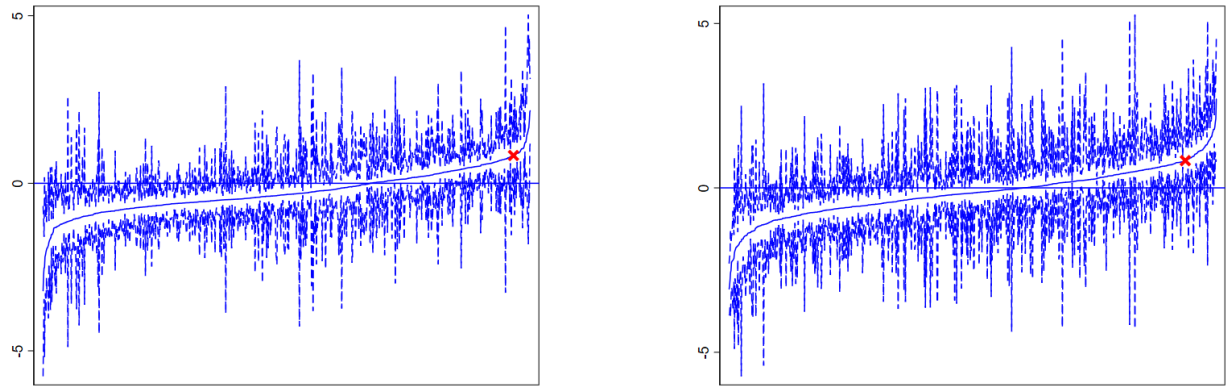
To carry out the placebo tests, we re-estimate (9) replacing $IV_{j,T}$ with *Placebo IV1*$_{i,T}$ or *Placebo IV2*$_{i,T}$, constructed from the two randomizations described above. Figure 4 shows the distribution of the 1,000 estimated β_1 coefficients with their 99% confidence intervals for the two types of placebo tests. The red cross corresponds to the estimated coefficient in our baseline regression (column 1 of Table 3), which is positive and significant at the 1% level. By contrast, randomizing the identity of swing states produces a wide range of coefficients, which are on average close to zero.

[41] As mentioned before, we classify states to be swing in a term based on the outcome of the presidential elections at the end of that term. The relevant elections for our sample period are thus 1992-2016.

[42] The variable *Placebo IV1*$_{i,T}$ is constructed by replacing the dummy variable *Swing State*$_{s,T}$ in equations (4) and 8 with *Placebo Swing State 1*$_{s,T}$.

[43] The variable *Placebo IV2*$_{i,T}$ is constructed by replacing the dummy variable *Swing State*$_{s,T}$ in equations (4) and 8 with *Placebo Swing State2*$_{s,T}$.

Figure 4
Estimated coefficients of *Placebo* $IV_{i,T}$



The figure plots the β_1 coefficients (with 99% confidence intervals) obtained from 1,000 randomizations of the swing states generating *Placebo* $IV1_{i,T}$ (panel (a)) and *Placebo* $IV2_{i,T}$ (panel (b)). The red cross corresponds to the estimated coefficient of $IV_{i,T}$ in column 1 of Table 3.

7 Effects of Politically Motivated Trade Protection

In this section, we use our instrument for AD duties to examine the effects of politically motivated trade protection. We first 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. We next study the mechanism behind these distributional effects, showing that trade protection decreases imports and increases prices in protected industries, raising production costs in downstream industries.

7.1 Employment Effects

7.1.1 Main Results

We first examine the employment effects of politically motivated trade protection in directly and indirectly exposed manufacturing industries. We focus on first terms, during which the incumbent president has incentives to manipulate trade protection for re-election purposes, and estimate the following regression by 2SLS:

$$\begin{aligned}\Delta L_{j,T} &= \beta_0 + \beta_1 \textit{Direct Tariff Exposure}_{j,T} + \beta_2 \textit{Downstream Tariff Exposure}_{j,T} \\ &\quad + \beta_3 \textit{Upstream Tariff Exposure}_{j,T} + Z_{j,T} + \delta_j + \delta_T + \varepsilon_{j,T}, \end{aligned} \tag{11}$$

where $\Delta L_{j,T}$ is the growth rate of employment in SIC4 industry j during term T.[44] 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 not only for time-invariant industry characteristics, but also for (linear) sectoral trends (e.g., the extent to which an industry is declining or being automated). The tariff exposure variables are defined in equations (1)-(3).[45] We instrument these variables with the corresponding IV measures: direct exposure is instrumented by $IV_{j,T}$, downstream exposure by *Downstream* $IV_{j,T} \equiv \sum_{i=1}^{N} \omega_{i,j} IV_{i,T}$, and the upstream exposure by *Upstream* $IV_{j,T} \equiv \sum_{i=1}^{N} \theta_{i,j} IV_{i,T}$. 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 vector $Z_{j,T}$ of the corresponding swing industry variables not interacted with AD experience.[46]

The results of estimating (11) are reported in columns 1 and 2 of Table 4. In the baseline specification of column 1, we include the diagonal of the input-output matrix ($\omega_{j,j}$ and $\theta_{j,j}$) when constructing *Downstream Tariff Exposure*$_{j,T}$ and *Upstream Tariff Exposure*$_{j,T}$ to account for input-output linkages both between and within industries. In column 2, we exclude the diagonal. The last row of Table 4 reports the Kleibergen-Paap (KP) F-statistics, a version of the Cragg-Donald statistic adjusted for clustered robust standard errors. This is always above the critical value of 7 (with multiple endogenous variables) based on a 10% maximal IV size, indicating that our instruments are strong.[47]

The coefficient of *Direct Tariff Exposure*$_{j,T}$ is positive and significant, indicating that AD duties foster employment growth in protected industries. In term of magnitude, the estimates in column 1 imply that a one standard deviation (0.139) increase in *Direct Tariff Exposure*$_{j,T}$ increases the growth rate of employment in protected industries by 3.0 percentage points, explaining around 14% of the standard deviation of employment growth in those industries. It should be stressed that AD duties are imposed on products, while our tariff exposure measures are defined at the more aggregate SIC4 level (since product-level employment data are not available). If the within-industry downstream effects are large, this can lead the estimated coefficient of *Direct Tariff Exposure*$_{j,T}$ to be downward biased.[48]

[44] For term T ending in year t, $\Delta L_{j,T} = \ln(Employment_{j,t}) - \ln(Employment_{j,t-4})$.

[45] These variables are expressed in levels. Recall, however, that their variation reflects policy changes (the imposition of new AD duties and the revocation or renewal of old duties).

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

[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-11; the coefficients of the instruments have the same signs as in Table 4.

[48] As an example, consider industry SIC 3312 ("Blast furnaces and steel mills"), which includes 235 HS6 products. In 2001, the United States introduced an AD duty against China on hot rolled steel products, covering products under 27 different HS6 lines, all belonging to the same industry (SIC 3312). Hot rolled

Looking at the effects along supply chains, the coefficient of *Downstream Tariff Exposure*$_{j,T}$ is negative and significant, while that of *Upstream Tariff Exposure*$_{j,T}$ is not significant. Thus AD duties decrease the growth rate of employment of industries that use the protected goods as inputs. Based on the estimates in column 1, a one standard deviation (0.081) increase in *Downstream Tariff Exposure*$_{j,T}$ decreases the growth rate of employment by 8.5 percentage points, explaining around 39% of the standard deviation of employment growth.

Table 4

The Effects on Trade Protection on Employment Along Supply Chains

	Manufacturing Industries		All industries	
	(1)	(2)	(3)	(4)
Direct Tariff Exposure$_{j,T}$	0.217**	0.187**		
	(0.092)	(0.092)		
Downstream Tariff Exposure$_{j,T}$	-1.059**	-0.972**	-1.177***	-1.163***
	(0.526)	(0.460)	(0.421)	(0.439)
Upstream Tariff Exposure$_{j,T}$	0.338	0.361	0.351	0.166
	(0.310)	(0.415)	(0.305)	(0.267)
Sector Fixed Effects	Yes	Yes	Yes	Yes
Term Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,567	1,567	1,915	1,915
KP F-statistic	13.6	11.9	29.2	27.1

Columns 1-2 report 2SLS estimates of equation (11), while columns 3-4 report 2SLS estimates of equation (12). 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 column 1 and 3 (2 and 4), *Downstream Tariff Exposure*$_{j,T}$ and *Upstream Tariff Exposure*$_{j,T}$ include (exclude) the diagonal of the input-output matrix. The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). In columns 1-2 (3-4), the sample includes all manufacturing sectors (all sectors) and covers all first terms during 1988-2016. 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.

AD duties can affect not only manufacturing sectors, but also other sectors indirectly exposed to trade protection. For example, higher duties on imports of steel may negatively affect producers in manufacturing (e.g., motor vehicles) and non-manufacturing (e.g., construction) sectors that use steel as an input. To examine the effects of politically-motivated

steel is an input in the production of other HS6 goods included in SIC 3312 that were not covered by AD duties, such as tramway rails (HS 730210).

protection in the entire US economy, we include all industries and estimate

$$\Delta L_{j,T} = \beta_0 + \beta_1 \textit{Downstream Tariff Exposure}_{j,T} + \beta_2 \textit{Upstream Tariff Exposure}_{j,T} + \delta_j + \delta_T + \varepsilon_{j,T}. \tag{12}$$

Notice that the variable *Direct Tariff Exposure* cannot be included in these regressions, since it cannot be defined for non-tradable industries. The results of estimating (12) are reported in columns 3 and 4 of Table 4. The coefficient of *Downstream Tariff Exposure*$_{j,T}$ remains negative and significant, and that of *Upstream Tariff Exposure*$_{j,T}$ remains insignificant. These findings confirm that politically motivated trade protection has a negative effect on US employment along supply chains: it reduces employment growth in downstream industries, without any significant gains in upstream sectors. The estimates reported in column 3 imply that one standard deviation (0.068) increase in *Downstream Tariff Exposure*$_{j,T}$ decreases the growth rate of employment by 8.0 percentage points, explaining around 36% of the standard deviation of employment growth.

The estimates in Table 4 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 noteworthy to compare the 2SLS estimates of Table 4 with the corresponding OLS estimates in Table A-10. As discussed at the start of Section 6, we expect the OLS estimates to be downward biased (in absolute value) due to omitted variables. In line with this argument, the coefficients for *Direct Tariff Exposure*$_{j,T}$ in Table A-10 are close to zero and not statistically significant; the coefficients of *Downstream Tariff Exposure*$_{j,T}$ have the correct sign, but are much smaller in magnitude compared to Table 4 and are only significant in two specifications.

One may expect the employment effects of trade protection to vary between blue- and white-collar workers. To verify this, we use data from the NBER-CES Manufacturing Industry Database to study the effects of AD duties on different types of workers. We replace the dependent variable in (11) with Δ*Production Workers*$_{j,T}$ or Δ*Non-Production Workers*$_{j,T}$, with measure the growth rate of blue-collar and white-collar jobs in SIC4 industry j during electoral term T.[49] The results reported in Table A-12 show that politically-motivated trade protection has positive effects on both blue-collar and white-collar workers in protected industries. The negative employment effects in downstream industries are confined

[49] We cannot do the same for equation (12), since data on blue-collar and white-collar jobs is only available for manufacturing sectors.

to blue-collar jobs.

7.1.2 Robustness Checks

We have carried out a series of additional estimations to verify the robustness of the results of Table 4. The most important check concerns our identification strategy. In our baseline estimates, we take the industry exposure shares (employment, AD experience, and input-output coefficients) to be exogenous, conditional on industry fixed effects. One may be concerned about the endogeneity of these shares. 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 can 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. We perform two types of randomization among the 26 states classified as swing at least once during our sample period (the same used to produce the placebo tests in Section 6.4). In the first one, we fix the number of times in which a state is swing to be the same as in Figure 2. 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 *Placebo Swing State1*$_{s,T}$, which we use to construct *Placebo IV1*$_{s,T}$. By averaging across the 1,000 draws, we obtain *Expected IV1*$_{j,T}$. In the second type of randomization, we fix the number of swing states in a given term to be as in Figure 2. Again, we perform 1,000 randomizations, each generating *Placebo Swing State2*$_{s,T}$, which we use to construct *Placebo IV2*$_{s,T}$. By averaging across randomizations, we obtain *Expected IV2*$_{j,T}$.

Table A-13 shows that our baseline results on the employment effects of trade protection are robust to addressing concerns about OVB: independently of the type of randomization used to construct the expected instruments, the coefficients of *Direct Tariff Exposure*$_{j,T}$ (*Downstream Tariff Exposure*$_{j,T}$) remain positive (negative) and significant, and are statistically different from the estimates reported in Table 4.

A series of additional estimations confirm the robustness of our results on the employment effects of politically-motivated protection. GATT/WTO rules allow for two 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 (Blonigen and Prusa, 2016). Table A-14 shows that the results are unaffected if we further include countervailing duties and safeguards.

In Table A-15, we control for additional tariffs. These include the MFN tariffs applied by the United States to industry j's imports ($MFN_{j,T}$), as well as the corresponding tariffs applied to j's input industries (*Downstream MFN Exposure*$_{j,T}$) and output industries (*Upstream MFN Exposure*$_{j,T}$). To account for possible retaliatory effects, we also include AD duties applied by China on US protected sectors (*Retaliation*$_{j,T}$) and those vertically related to them (*Downstream Retaliation*$_{j,T}$ and *Upstream Retaliation*$_{j,T}$). The coefficients of the variables *Direct Tariff Exposure*$_{j,T}$ and *Downstream Tariff Exposure*$_{j,T}$ remain significant at the 1% level, while the coefficients of the additional tariff variables are not significant.

7.2 Mechanisms

The results reported in Table 4 show that politically motivated protection fosters employment growth in protected sectors, but decreases growth in downstream sectors. In what follows, we explore the mechanisms behind these effects, examining the impact of AD duties on imports and prices in protected industries, as well as on input prices faced by producers in downstream industries.

We first study the effects of AD duties on imports in the sectors targeted by trade protection. To this purpose, we use data from the United Nations (UN) Comtrade database to construct the variable Δ*Imports*$_{j,T}$, the growth rate of US imports in industry j during term T.[50] As in equation (11), we focus on first terms, during which the incumbent president has incentives to manipulate trade protection for re-election purposes. *Direct Tariff Exposure*$_{j,T}$ is instrumented with $IV_{j,T}$. We control for the variable *Swing Industry*$_{j,T}$ (coefficient not reported) to account for the possible effects of other policies, and include sector and term fixed effects. The results reported in column 1 of Table 5 indicate that AD duties decrease US imports in targeted industries.

In column 2, we examine the effects on import prices. In this specification, the dependent variable is Δ*Imports Price*$_{j,T}$, the growth rate of import prices in SIC4 industry j during term T.[51] The estimates show that AD protection increases import prices in targeted sectors. Column 3 considers the effects on US producer prices. Using data on producer

[50] Comtrade provides import values at the HS6 level. We convert the data to the SIC4 level using the HS1992-SIC4 concordance files.

[51] To construct import prices, we first obtain data on unit values from Comtrade at the HS6 level. We then convert them at the SIC4 level, weighting the prices of HS6 products by their import values in year t.

price indices (PPI) from the US Bureau of Labor Statistics (BLS), we construct the variable Δ*Producer Price*$_{j,T}$, the growth rate of the prices in SIC4 industry j during term T.[52] The results indicate that AD protection increases producer prices in the protected industries. Overall, the results of Table 5 provide evidence for the mechanisms behind the positive employment effects of AD duties on protected industries documented in Table 4.

Table 5
The Effects of Trade Protection on Imports and Prices

	Import values	Import prices	Producer prices
	(1)	(2)	(3)
Direct Tariff Exposure$_{j,T}$	-3.119**	0.367**	0.294***
	(1.459)	(0.176)	(0.069)
Sector FE	Yes	Yes	Yes
Term FE	Yes	Yes	Yes
Observations	1,120	1,120	1,170
KP F-statistic	17.4	17.4	20.6

The reports 2SLS estimates. In column 1 (2), the dependent variable is Δ*Imports*$_{j,T}$ (Δ*Imports Price*$_{j,T}$) the growth rate of the value (the prices of) of US imports from China in SIC4 industry j during term T. In column 3, the dependent variable is Δ*Producer Price*$_{j,T}$, the growth rate of US producer prices in SIC4 industry j during term T. *Direct Tariff Exposure*$_{j,T}$ AD protection in protected industries and is instrumented using the corresponding IV variable. The sample covers all executive first terms during 1988-2016 and includes all manufacturing sectors. All regressions include the corresponding *Swing Industry* variable (coefficients not reported). 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 consider the mechanisms behind the negative employment effects of trade protection on downstream industries. To this purpose, we combine PPI data from the BLS with input-output data from the BEA to construct the variable Δ*Input Price*$_{j,T}$, which measures the change in the price of inputs used by industry j during term T.[53] The results are reported in Table 6. As in Table 4, we consider first the effects of trade protection on input princes in manufacturing industries (columns 1-2) and then on all industries (columns 3-4) and report estimates with and without the diagonal of the input output matrix. Across all specifications, the coefficient of *Downstream Tariff Exposure*$_{j,T}$ is positive and significant at the 1% level, indicating that politically motivated tariffs raise input prices for producers

[52]We create a harmonized price index by normalizing industry prices to 100 for the year 2000.

[53]This variable is constructed by weighting PPI prices with the cost shares from the BEA input-output tables, i.e., *Input Price*$_{j,t} = \sum_{i=1}^{N} \omega_{i,j}$*Price*$_{i,t}$, where $\omega_{i,j}$ is the cost share of input i in the production of j.

in downstream industries. These results provide evidence for the mechanisms behind the negative effects of AD protection on downstream industries documented in Table 4.

Table 6
The Effects of Trade Protection on Input Prices

	Manufacturing Industries		All Industries	
	(1)	(2)	(3)	(4)
Downstream Tariff Exposure$_{j,T}$	0.866***	0.936***	0.598***	0.682***
	(0.151)	(0.167)	(0.087)	(0.089)
Sector FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes
Observations	1,568	1,568	1,916	1,916
KP F-statistic	25.4	21.5	49.5	41.9

The table reports 2SLS estimates. The dependent variable is Δ*Input Price*$_{j,P}$, the change in the price of inputs used by industry j during term T. *Downstream Tariff Exposure*$_{j,T}$ captures exposure to trade protection by downstream industries and is instrumented by the corresponding IV measures. In columns 1 and 3 (2 and 4), Δ*Input Price*$_{j,P}$ and *Downstream Tariff Exposure*$_{j,T}$ include (exclude) the diagonal of the input-output matrix. In columns 1 and 2 (3 and 4), the sample includes all manufacturing sectors (all sectors) and covers all first terms during 1988-2016. All regressions include the corresponding *Swing Industry* variable (coefficients not reported). 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.

8 Conclusion

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 leading to undemocratic outcomes. Indeed, several US presidents have come into office despite earning fewer votes nationally than the loser.

This Electoral College system has also been criticized for giving tremendous 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 downstream industries.

We first show that swing-state politics shapes US antidumping (AD) duties, the most commonly used trade policy barrier. In line with the theoretical model of Conconi *et al.* (2017), the effects are confined to executive first terms, during which the incumbent president can be re-elected.

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. Our identification relies on changes in the identity of swing states across electoral terms, which generate exogenous political shocks. Exposure to these shocks varies across industries, depending on their geographic distribution across states (at the start our sample) and on their historical (pre-sample) experience in dealing with the complex AD proceedings. This instrument strongly predicts variation in AD protection during first terms, when the president can be re-elected. We also provide micro-level evidence in line with our identification strategy: during first terms, our instrument predicts support for trade protection by ITC commissioners appointed by the party of the president.

We find that politically motivated protection generates winners and losers across industries. It fosters employment growth in protected industries, but hinder growth in downstream industries. We further provide evidence for the mechanisms behind these effects: AD duties decrease imports and raise prices in protected industries, increasing input prices for producers in downstream industries. These findings resonate with concerns often heard in the media about the costs of protection along supply chains.[54]

Our analysis provides new arguments in the ongoing debate about the need to reform the Electoral College system. It implies that, if this system were to be abolished and all votes counted equally in US presidential elections, key input industries (e.g., blast furnaces and steel mills, motor vehicle parts and accessories) would receive lower trade protection, with beneficial effects 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 "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

[54]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).

the spirit of Bagwell and Staiger, 2005): incumbent politicians can use these measures to favor particular industries and increase their chances to retain power.

References

Adão, R. M. Kolesar, and E. Morales (2019). "Shift-Share Designs: Theory and Inference," *Quarterly Journal of Economics* 134, 1949-2010.

Alesina, A., and N. Roubini (1992). "Political Cycles in OECD Economies," *Review of Economic Studies* 59, 663-688.

Alfaro, L., P. Antràs, D. Chor, and P. Conconi (2019). "Internalizing Global Value Chains: A Firm-Level Analysis," *Journal of Political Economy* 127, 508-559.

Alfaro, L., M. X. Chen, and D. Chor (2023). "Can Evidence-Based Information Shift Preferences Towards Trade Policy?" NBER WP No. 31240.

Alfaro, L., P. Conconi, H. Fadinger, and A. F. Newman (2016). "Do Prices Determine Vertical Integration?" *Review of Economic Studies* 83, 855-888.

Amiti, M., and J. Konings (2007). "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia," *American Economic Review* 97, 1611-1638.

Amiti, M., S. J. Redding, and D. E. Weinstein (2019). "The Impact of the 2018 Trade War on U.S. Prices and Welfare," *Journal of Economic Perspectives* 33, 187-210.

Angrist, J. D., and J. S. Pischke (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Antràs, P., and D. Chor (2022). "Global Value Chains," in Gopinath, G., E. Helpman, and K. Rogoff, *Handbook of International Economics* Vol. 5.

Antràs, P., D. Chor, T. Fally, and R. Hillberry (2012). "Measuring the Upstreamness of Production and Trade Flows," *American Economic Review Papers & Proceedings* 102, 412-416.

Antràs, P., T. Fort, and F. Tintelnot (2017). "The Margins of Global Sourcing: Theory and Evidence from US," *American Economic Review* 107, 2514-2564.

Aquilante, T. (2018). "Undeflected Pressure? The Protectionist Effect of Political Partisanship on US Antidumping Policy," *European Journal of Political Economy* 55, 455-470.

Autor, D. H., D. Dorn, and G. H. Hanson (2013). "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review* 103, 2121-2168.

Autor, D. H., D. Dorn, G. H. Hanson, and K. Majlesi (2020a). "Importing Political Polarization? The Electoral Consequences of Rising Trade Exposure," *American Economic Review* 110, 3139-3183.

Bagwell, K., and R. W. Staiger (1990). "A Theory of Managed Trade," *American Economic Review* 80, 779-795.

Bagwell, K., and R. W. Staiger (2005). "Enforcement, Private Political Pressure and the GATT/WTO Escape Clause," *The Journal of Legal Studies* 34, 471-513.

Barattieri, A., and M. Cacciatore (2023). "Self-Harming Trade Policy? Protectionism and Production Networks," *American Economic Journal: Macroeconomics* 15, 97-128.

Bartik, T. J. (1991). "Who Benefits from State and Local Economic Development Policiescies?" WE Upjohn Institute for Employment Research.

Besedes, T., and T. J. Prusa (2017). "The Hazardous Effect of Antidumping," *Economic Inquiry* 55, 9-30.

Blaum, J., C. Lelarge, and M. Peters (2018). "The Gains from Input Trade with Heterogeneous Importers," *American Economic Journal: Macroeconomics* 10, 77-127.

Blonigen, B. A. (2002). "Tariff-Jumping Antidumping Duties," *Journal of International Economics* 57, 31-49.

Blonigen, B. A. (2006). "Working the System: Firm Learning and the Antidumping Process," *European Journal of Political Economy* 22, 715-731.

Blonigen, B. A. (2016). "Industrial Policy and Downstream Export Performance," *Economic Journal* 126, 1635-1659.

Blonigen, B. A., and J. H. Park (2004). "Dynamic Pricing in the Presence of Antidumping Policy: Theory and Evidence," *American Economic Review* 94, 134-154.

Blonigen, B. A., and T. J. Prusa (2003). "Antidumping," in E. K. Choi and J. Harrigan (eds.), *Handbook of International Economics*, 251-284. Blackwell Publishing,

Blonigen, B. A., and T. J. Prusa (2016). "Dumping and Antidumping Duties," in K. Bagwell, and R. W. Staiger (eds), *Handbook of Commercial Policy* Volume 1B, 107-159. Elsevier.

Borusyak, K., and P. Hull (2023). "Non-Random Exposure to Exogenous Shocks: Theory and Applications," *Econometrica*, forthcoming.

Borusyak, K., P. Hull, and X. Jaravel (2022). "Quasi-Experimental Shift-Share Research Designs," *Review of Economic Studies* 89, 181-213.

Bown, C. P., M. Cieszkowsky, A. Erbahar, and J. Signoret (2020). Temporary Trade Barriers Database.

Bown, C. P., and M. A. Crowley (2007). "Trade Deflection and Trade Depression," *Journal of International Economics* 72, 176-201.

Bown, C. P., and M. A. Crowley (2013). "Self-Enforcing Trade Agreements: Evidence from Time-Varying Trade Policy," *American Economic Review* 103, 1071-1090.

Bown, C. P., A. Erbahar, and M. Zanardi (2021). "Global Value Chains and the Removal of Trade Protection," *European Economic Review* 140, 103937.

Brainard, S. L., and T. Verdier (1997). "The Political Economy of Declining Industries: Senescent Industry Collapse Revisited," *Journal of International Economics* 42, 221-237.

Cavallo, A., G. Gopinath, B. Neiman, and J. Tang (2019). "Tariff Passthrough at the Border and at the Store: Evidence from US Trade Policy," *American Economic Review: Insights* 3, 19-34.

Che, Y., Y. Lu, J. Pierce, P. Schott, and Z. Tao (2022). "Did Trade Liberalization with China Influence U.S. Elections?," *Journal of International Economics* 139.

Conconi, P., D. DeRemer, G. Kirchsteiger, L. Trimarchi, and M. Zanardi (2017). "Suspiciously Timed Trade Disputes," *Journal of International Economics* 105, 57-76.

Conconi, P., M. García-Santana, L. Puccio, and R. Venturini (2018). "From Final Goods to Inputs: The Protectionist Effect of Rules of Origin," *American Economic Review* 108, 2335-2365.

Debaere, P. M. (2009). "Fishy Issues: The U.S. Shrimp Antidumping Case," Darden Case No. UVA-G-0600.

Drazen, A. (2000). "The Political Business Cycle after 25 Years," *NBER Macroeconomics Annual* 15 75-117.

Erbahar, A., and Y. Zi (2017). "Cascading Trade Protection: Evidence from the US," *Journal of International Economics* 108, 274-299.

Fajgelbaum, P. D., P. K. Goldberg, P. J. Kennedy, and A. Khandelwal (2020). "The Return to Protectionism," *Quarterly Journal of Economics* 135, 1-55.

Feenstra, R. C. (1996). "US Imports, 1972-1994: Data and Concordances," NBER Working Paper No. 5515.

Ferraz, C., and F. Finan (2011). "Electoral Accountability and Corruption: Evidence from the Audits of Local Governments," *American Economic Review* 101, 1274-1311.

Finger, J. M., H. K. Hall, and D. R. Nelson (1982). "The Political Economy of Administered Protection," *American Economic Review* 72, 452-466.

Flaaen, A., A. Hortaçsu, and F. Tintelnot (2020). "The Production Relocation and Price Effects of U.S. Trade Policy: The Case of Washing Machines," *American Economic Review* 110(7), 2103-27.

Flaaen, A., and J. Pierce (2019). "Disentangling the Effects of the 2018-2019 Tariffs on a Globally Connected U.S. Manufacturing Sector," FEDS Working Paper 2019-086.

Gallaway, M. P., B. A. Blonigen, and J. E. Flynn (1999). "Welfare Costs of the US Antidumping and Countervailing Duty Laws," *Journal of International Economics* 49, (1999): 211-244.

Goldberg, P. K., A. Khandelwal, N. Pavcnik, and P. Topalova (2010). "Imported Intermediate Inputs and Domestic Product Growth: Evidence from India," *Quarterly Journal of Economics* 125, 1727-1767.

Goldsmith-Pinkham, P., I. Sorkin, and H. Swift (2020). "Bartik Instruments: What, When, Why, and How," *American Economic Review* 110, 2586-2624.

Halpern, L., M. Koren, and A. Szeidl (2015). "Imported Inputs and Productivity," *American Economic Review* 105, 3660-3703.

Hansen, W. L., and T. J. Prusa (1997). "The Economics and Politics of Trade Policy: An Empirical Analysis of ITC Decision Making," *Review of International Economics* 5, 230-245.

Imbens, G. W., and J. D. Angrist (1994). "Identification and Estimation of Local Average Treatment Effects," *Econometrica* 62, 467-475.

Irwin, D. A. (2005). "The Rise of US Anti-dumping Activity in Historical Perspective," *The World Economy* 28, 651-668.

Jabbour, L., Z. Tao, E. Vanino, and Y. Zhang (2019). "The Good, the Bad and the Ugly: Chinese Imports, European Union Anti-dumping Measures and Firm Performance," *Journal of International Economics* 117, 1-20.

Konings, J., and H. Vandenbussche (2008). "Heterogeneous Responses of Firms to Trade Protection," *Journal of International Economics* 76, 371-383.

Kovak, B. K. (2013). "Regional Effects of Trade Reform: What Is the Correct Measure of Liberalization?" *American Economic Review*, 103, 1960-1976.

Lu, Y., Z. Tao, and Y. Zhang (2013). "How do Exporters Respond to Antidumping Investigations?" *Journal of International Economics* 9, 290.

Ma, X., and J. McLaren (2018). "A Swing-State Theorem, with Evidence," NBER Working Paper No. 24425.

Moore, M. (1992). "Rules or Politics? An Empirical Analysis of Antidumping Decisions," *Economic Inquiry* 30, 449-466.

Muûls, M., and D. Petropoulou (2013). "A Swing State Theory of Trade Protection in the Electoral College," *Canadian Journal of Economics* 46, 705-724.

Navarra, E. (2023). "The Effects of Corporate Subsidies Along Value Chains," mimeo, ECARES.

Persson, T., G. Roland, and G. Tabellini (1997). "Separation of Powers and Political Accountability," *Quarterly Journal of Economics* 112, 1163-1202.

Persson, T., G. Tabellini, and F. Trebbi (2003). "Electoral Rules and Corruption," *Journal of the European Economic Association* 1, 958-989.

Persson, T., and G. Tabellini (2004). "Constitutional Rules and Fiscal Policy Outcomes," *American Economic Review* 94, 25-45.

Pierce, J. R. (2011). "Plant-Level Responses to Antidumping Duties: Evidence from U.S. Manufacturers," *Journal of International Economics* 85, 222-233.

Pierce, J. R., and P. K. Schott (2016). "The Surprisingly Swift Decline of US Manufacturing Employment," *American Economic Review* 106, 1632-1662.

Prusa, T. J. (1997). "The Trade Effects of U.S. Antidumping Actions," in R. C. Feenstra (ed.), *Effects of U.S. Trade Protection and Promotion Policies*. Chicago: University of Chicago Press.

Prusa, T. J. (2001). "On the Spread and Impact of Antidumping," *Canadian Journal of Economics*, 34, 591-611.

Rogoff, K. (1990). "Equilibrium Political Business Cycles," *American Economic Review* 80, 21-36.

Rogoff, K. and A. Sibert (1988). "Elections and Macroeconomic Policy Cycles," *Review of Economic Studies* 55, 1-16.

Strömberg, D. (2008). "How the Electoral College Influences Campaigns and Policy: The Probability of Being Florida," *American Economic Review* 98, 769-807.

Topalova, P. (2010). "Factor Immobility and Regional Impacts of Trade Liberalization: Evidence on Poverty from India," *American Economic Journal: Applied Economics* 2, 1-41.

Trefler, D. (1993). "Trade Liberalization and the Theory of Endogenous Protection: An Econometric Study of U.S. Import Policy," *Journal of Political Economy* 101, 138-160.

Vandenbussche, H., and C. Viegelahn (2018). "Input Reallocation Within Multi-Product Firms," *Journal of International Economics* 114, 63-79.

Vandenbussche, H., and M. Zanardi (2010). "The Chilling Trade Effects of Antidumping Proliferation," *European Economic Review* 54 760-777.

Yi, K-M. (2003). "Can Vertical Specialization Explain the Growth of World Trade?" *Journal of Political Economy* 111, 52-102.

Appendices

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:[55]

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.[56] 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.

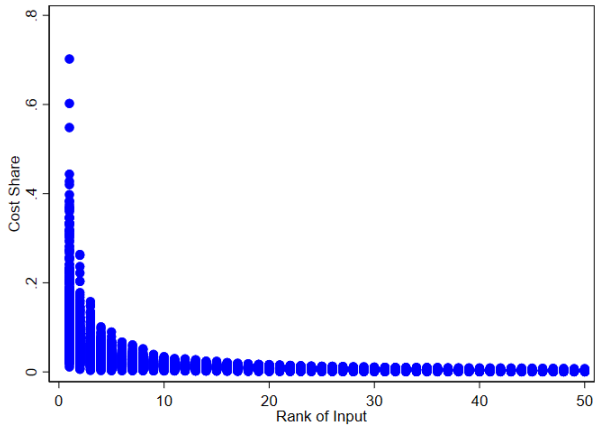
[55]Throughout, when we refer to SIC industries, we use the "sic87dd" scheme used by Autor *et al.* (2013). These codes are slightly coarser than the 1987 SIC codes.

[56]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), available at http://cid.econ.ucdavis.edu/usix.html.

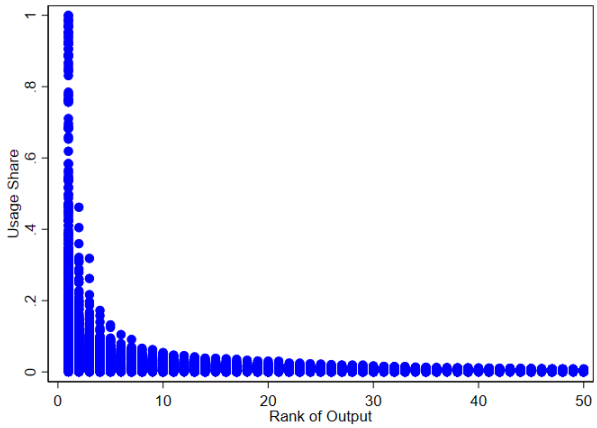
A-2 Descriptive Statistics

Figure A-1
Distribution of IO coefficients

(a) Top-50 input industries

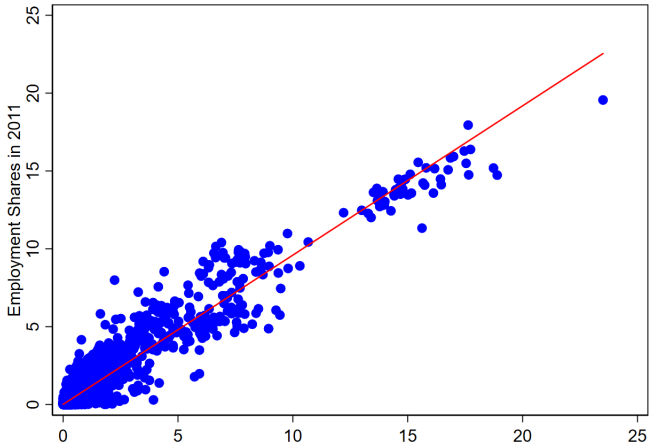


(b) Top-50 output industries



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

Figure A-2
SIC4 employment shares by state



The figure plots state-level industry employment shares in 1988 and 2016, based on CBP data.

Table A-1

Top 10 input industries

SIC4	Input industry	Number of output industries	Average cost share
		(1)	(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 AD duties applied by the United States against China

Variable	Obs.	Mean	Std. dev.	Min	Max
Direct Tariff Exposure$_{j,t}$	2,742	0.127	0.333	0.000	1.000
Downstream Tariff Exposure$_{j,t}$	2,742	0.152	0.115	0.002	0.647
Upstream Tariff Exposure$_{j,t}$	2.742	0.090	0.153	0.000	1.463

The table reports descriptive statistics of the tariff exposure variables (defined in equations (1)-(3)). The variables *Downstream Tariff Exposure*$_{j,t}$ and *Upstream Tariff Exposure*$_{j,t}$ account for direct and indirect input-output linkages and include the diagonal of the input-output matrix. The sample covers 1988-2016 and includes all manufacturing industries.

Table A-3

Descriptive statistics of $IV_{j,T}$, *Swing Industry*$_{j,T}$ and *AD Experience*$_j$

Variable	Obs.	Mean	Std. dev.	Min	Max
Swing Industry$_{j,T}$	2,742	0.003	0.004	0.000	0.054
AD Experience$_j$	2,742	1.233	3.605	0.000	63.000
$IV_{j,T}$	2,742	0.008	0.072	0.000	1.942

The table reports descriptive statistics of our instrument for AD protection, $IV_{j,T}$ (defined in (8)) and of its components, *Swing Industry*$_{j,T}$ (defined in (4)) and *AD Experience*$_j$ (defined in (5)).

Table A-4

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

Swing Industry$_{j,T}$

Sector	Description	Average *Swing Industry*$_{j,T}$	Average *Direct Tariff Exposure*$_{j,T}$
3714	Motor vehicle parts and accessories	0.031	0.714
3089	Plastics products, n.e.c.	0.031	0.286
2752	Commercial printing, lithographic	0.030	0.429
2599	Furniture and fixtures, n.e.c.	0.023	0.571
2711	Newspapers	0.023	0.000
3711	Motor vehicles and car bodies	0.022	0.000
3312	Blast furnaces and steel mills	0.020	0.571
3499	Fabricated metal products, n.e.c.	0.016	1.000
3599	Industrial machinery, n.e.c.	0.014	0.286
3812	Search and navigation equipment	0.013	0.000

AD Experience$_j$

Sector	Description	*Experience*$_j$	Average *Direct Tariff Exposure*$_{j,T}$
3312	Blast furnaces and steel mills	63	0.571
2819	Industrial inorganic chemicals, n.e.c.	13	1.000
3714	Motor vehicle parts and accessories	12	0.714
2869	Industrial organic chemicals, n.e.c.	10	1.000
3999	Manufacturing industries, n.e.c.	8	1.000
2821	Plastics materials and resins	7	1.000
3494	Valves and pipe fittings, n.e.c.	7	1.000
3991	Brooms and brushes	7	1.000
3496	Misc. fabricated wire products	7	0.857
2399	Fabricated textile products, n.e.c.	7	0.286

The table lists the top-15 SIC4 sectors with the highest average value of the variable *Swing Industry*$_{j,T}$ (defined in (4)) during 1988-2016 (top panel) and the highest value of *AD Experience*$_j$ (defined in (5)) in 1980-1987 (bottom panel), with the corresponding average AD protection.

A-3 Additional Results and Robustness Checks

Table A-5
Swing-State Politics and AD Protection
(Second Terms)

	AD dummy	Product share	All TTBs	All industries
	(1)	(2)	(3)	(4)
Swing Industry$_{j,T}$	-2.581	1.408	3.105	-8.197
	(18.353)	(3.103)	(18.085)	(79.289)
Sector FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.56	0.49	0.56	0.56
Observations	1,176	1,176	1,176	1,176

The table reports OLS estimates of equation (6). In columns 1, and 4, the dependent variable is *Trade Protection*$_{j,T}$, a dummy variable equal to 1 if products in SIC4 industry j are covered by AD duties during term T; in column 2, it is the average share of products in SIC4 industry j covered by AD duties during term T; in column 3, it is a dummy variable equal to 1 if products in SIC4 industry j are covered by any TTB (AD duties, countervailing duties, or safeguards) during term T. In columns 1, 2, 3, the denominator of the variable *Swing Industry*$_{j,T}$ includes all manufacturing industries; in column 4, it includes all industries. The sample includes manufacturing industries and covers all executive second terms during 1998-2016. 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

State-Level Characteristics and the Identity of Swing States
(Second Terms)

	(1)	(2)	(3)	(4)	(5)	(6)
Trade Protection$_{s,T}$	1.853					
	(11.887)					
Δ*Trade Protection*$_{s,T}$		-0.110				
		(0.165)				
Import Exposure$_{s,T}$			4.519			
			(7.943)			
Δ*Import Exposure*$_{s,T}$				-0.404		
				(0.272)		
Employment$_{s,T}$					-2.755	
					(3.222)	
Δ*Employment*$_{s,T}$						-0.015
						(0.076)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.64	0.64	0.64	0.65	0.64	0.64
Observations	150	150	150	150	150	150

The table reports OLS estimates of equation (7). *Trade Protection*$_{s,T}$ (Δ*Trade Protection*$_{s,T}$) captures (changes in) state-level trade protection during term T. *Import Exposure*$_{s,T}$ (Δ*Import Exposure*$_{s,T}$) captures (changes in) state-level exposure to import competition during term T. *Employment*$_{s,T}$ (*Employment Growth*$_{s,T}$) measures manufacturing employment (the growth rate of manufacturing employment) in state s during term T. The sample covers all executive second terms during 1988-2016. Standard errors in parentheses are clustered at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-7
IV and AD Protection
(Controlling for Swing Industry)

	AD dummy	Product share	All TTBs	All industries
	(1)	(2)	(3)	(4)
$IV_{j,T}$	0.685***	0.068***	0.671***	2.437***
	(0.161)	(0.007)	(0.160)	(0.640)
Swing Industry$_{j,T}$	5.001	0.026	-3.347	26.642
	(4.450)	(0.178)	(4.679)	(18.541)
Sector FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes
Observations	1,568	1,568	1,568	1,568
Adjusted R^2	0.56	0.50	0.54	0.56

The table reports OLS estimates. In columns 1 and 4, the dependent variable is *Trade Protection*$_{j,T}$, a dummy variable equal to 1 if products in SIC4 industry j are covered by AD duties during term T; in column 2, it is the average share of products in SIC4 industry j covered by AD duties during term T; in column 3, it is a dummy variable equal to 1 if products in SIC4 industry j are covered by any temporary trade barrier (AD duties, countervailing duty, or safeguards) during term T. In columns 1, 2, and 3, the denominator of the variable *Swing Industry*$_{j,T}$ includes all manufacturing industries; in column 4, it includes all industries. The sample includes manufacturing industries and covers all executive first terms during 1998-2016. 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
IV and AD Protection
(Second Terms)

	AD dummy	Product share	All TTBs	All industries
	(1)	(2)	(3)	(4)
$IV_{j,T}$	-1.074	-0.196	0.503	-3.751
	(0.864)	(0.207)	(0.681)	(3.567)
Sector FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes
Observations	1,176	1,176	1,176	1,176
Adjusted R^2	0.56	0.49	0.56	0.56

The table reports OLS estimates of equation (9). In columns 1 and 4, the dependent variable is *Trade Protection*$_{j,T}$, a dummy variable equal to 1 if products in SIC4 industry j are covered by AD duties during term T; in column 2, it is the average share of products in SIC4 industry j covered by AD duties during term T; in column 3, it is a dummy variable equal to 1 if products in SIC4 industry j are covered by any temporary trade barrier (AD duties, countervailing duty, or safeguards) during term T. In columns 1, 2, and 3, the denominator of the variable *Swing Industry*$_{j,T}$ includes all manufacturing industries; in column 4, it includes all industries. The sample includes manufacturing industries and covers all executive second terms during 1998-2016. 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
Predicting ITC votes on AD

	First terms	Second terms
	(1)	(2)
$IV_{j,T} \times$ *President's Party*$_{i,T}$	0.062**	0.017
	(0.029)	(0.041)
$IV_{j,T}$	-0.001	-0.697
	(0.731)	(0.471)
President's Party$_{i,T}$	0.061	0.066
	(0.076)	(0.050)
Commissioner FE	yes	yes
Sector FE	yes	yes
Year FE	yes	yes
Observations	884	519
Adjusted R^2	0.54	0.69

The table reports OLS estimates of regression (10). The dependent variable is $Vote_{i,c(j),t}$, a dummy variable which is equal to 1 if ITC commissioner i votes in favor of AD duties on case c (involving SIC4 industry j) in year t. The dummy variable *President's Party*$_{i,T}$ is equal to 1 if commissioner i has been appointed by the party of the president who is in office during term T. $IV_{j,T}$ is defined in equation (8). In column 1 (column 2) the sample includes all final AD votes cast by ITC commissioners during executive first (second) terms in the period 1988-2016. Sector fixed effects are defined at the SIC4 level. Standard errors in parentheses are clustered at the SIC3 industry level. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-10

Trade Protection and Employment Along Supply Chains

(OLS Estimates)

	Manufacturing industries		All industries	
	(1)	(2)	(3)	(4)
Direct Tariff Exposure$_{j,T}$	-0.017	-0.023		
	(0.025)	(0.025)		
Downstream Tariff Exposure$_{j,T}$	-0.163	-0.203	-0.293**	-0.316**
	(0.149)	(0.158)	(0.139)	(0.148)
Upstream Tariff Exposure$_{j,T}$	0.005	-0.022	-0.030	-0.054
	(0.109)	(0.109)	(0.112)	(0.106)
Sector FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes
Observations	1,567	1,567	1,915	1,915
Adjusted R^2	0.36	0.36	0.50	0.50

Columns 1-2 report OLS estimates of equation (11), while columns 3-4 report OLS estimates of equation (12). 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 equations (1)-(3). In column 1 and 3 (2 and 4), *Downstream Tariff Exposure*$_{j,T}$ and *Upstream Tariff Exposure*$_{j,T}$ include (exclude) the diagonal of the input-output matrix. The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). In columns 1-2 (3-4), the sample includes all manufacturing sectors (all sectors) and covers all first terms during 1988-2016. 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-11

Reduced-Form Results for Table 4

	Manufacturing industries		All industries	
	(1)	(2)	(3)	(4)
$IV_{j,T}$	0.153***	0.154**		
	(0.058)	(0.068)		
Downstream $IV_{j,T}$	-0.615**	-0.499**	-0.824**	-0.836**
	(0.276)	(0.241)	(0.338)	(0.354)
Upstream $IV_{j,T}$	0.316	0.416	0.565	0.301
	(0.430)	(0.531)	(0.450)	(0.439)
Sector FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes
Observations	1,567	1,567	1,915	1,915
Adjusted R^2	0.39	0.39	0.52	0.52

The table reports the reduced-form results of the 2SLS estimates of Table 4. 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 equations (1)-(3), and are instrumented using the corresponding IV measures. In column 1 and 3 (2 and 4), *Downstream Tariff Exposure*$_{j,T}$ and *Upstream Tariff Exposure*$_{j,T}$ include (exclude) the diagonal of the input-output matrix. The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). In columns 1-2 (3-4), the sample includes all manufacturing sectors (all sectors) and covers all first terms during 1988-2016. 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-12

The Effects on Trade Protection on Employment Along Supply Chains
(Production and Non-Production Workers)

	Production workers		Non-production workers	
	(1)	(2)	(3)	(4)
Direct Tariff Exposure$_{j,T}$	0.300**	0.288**	0.216**	0.240**
	(0.121)	(0.119)	(0.090)	(0.095)
Downstream Tariff Exposure$_{j,T}$	-1.161*	-1.177*	-0.771	-0.623
	(0.650)	(0.598)	(0.539)	(0.482)
Upstream Tariff Exposure$_{j,T}$	0.370	0.372	0.179	0.261
	(0.298)	(0.401)	(0.309)	(0.446)
Sector FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes
Observations	1,552	1,552	1,552	1,552
KP F-statistic	14.4	10.8	14.4	10.8

The table reports 2SLS estimates of equation (11). In columns 1-2 (3-4), the dependent variable is Δ*Production Workers*$_{j,T}$ (Δ*Non-Production Workers*$_{j,T}$), the log change of employment in blue-collar (white-collar) jobs in SIC4 industry j during term T. The tariff exposure variables defined in equations (1)-(3) are instrumented using the corresponding IV measures. In columns 1 and 3 (2 and 4), *Downstream Tariff Exposure*$_{j,T}$ and *Upstream Tariff Exposure*$_{j,T}$ include (exclude) the diagonal of the input-output matrix. All specifications include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). The sample includes all manufacturing sectors and covers all first terms during 1988-2016. 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-13

The Effects on Trade Protection on Employment Along Supply Chains
(Recentering the Instruments)

Recentering using first type of randomization of swing states				
	Manufacturing industries		All industries	
	(1)	(2)	(3)	(4)
Direct Tariff Exposure$_{j,T}$	0.219**	0.192**		
	(0.089)	(0.085)		
Downstream Tariff Exposure$_{j,T}$	-1.000*	-0.921**	-1.091***	-1.075**
	(0.516)	(0.446)	(0.400)	(0.417)
Upstream Tariff Exposure$_{j,T}$	0.333	0.356	0.352	0.167
	(0.301)	(0.400)	(0.300)	(0.265)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,567	1,567	1,915	1,915
KP F-statistic	13.9	13.6	33.9	32.5
Recentering using second type of randomization of swing states				
	Manufacturing industries		All industries	
	(1)	(2)	(3)	(4)
Direct Tariff Exposure$_{j,T}$	0.227**	0.200***		
	(0.089)	(0.072)		
Downstream Tariff Exposure$_{j,T}$	-0.975**	-0.911**	-1.014***	-1.006***
	(0.482)	(0.410)	(0.355)	(0.369)
Upstream Tariff Exposure$_{j,T}$	0.352	0.363	0.404	0.225
	(0.253)	(0.323)	(0.268)	(0.233)
Sector FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,567	1,567	1,915	1,915
KP F-statistic	9.52	14.7	45.2	44.8

Columns 1-2 report 2SLS estimates of equation (11), while columns 3-4 report 2SLS estimates of equation (12). 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 equations (1)-(3), instrumented using the corresponding IV variables. In the top (bottom) panel, the instruments are recentered using *Expected IV1*$_{j,T}$ (*Expected IV2*$_{j,T}$) and the corresponding downstream and upstream variables. In column 1 and 3 (2 and 4), *Downstream Tariff Exposure*$_{j,T}$ and *Upstream Tariff Exposure*$_{j,T}$ include (exclude) the diagonal of the input-output matrix. The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). In columns 1-2 (3-4), the sample includes all manufacturing sectors (all sectors) and covers all first terms during 1988-2016. 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-14

The Effects on Trade Protection on Employment Along Supply Chains

(All TTBs)

	Manufacturing industries		All industries	
	(1)	(2)	(3)	(4)
Direct Tariff Exposure$_{j,T}$	0.203**	0.152**		
	(0.087)	(0.066)		
Downstream Tariff Exposure$_{j,T}$	-1.156**	-1.038**	-1.113***	-1.110***
	(0.551)	(0.449)	(0.403)	(0.421)
Upstream Tariff Exposure$_{j,T}$	0.294	0.308	0.309	0.150
	(0.268)	(0.356)	(0.273)	(0.256)
Sector FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,567	1,567	1,915	1,915
KP F-statistic	8.61	10.2	28.0	23.4

Columns 1-2 report 2SLS estimates of equation (11), while columns 3-4 report 2SLS estimates of equation (12). 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 equations (1)-(3), instrumented using the corresponding IV variables. In column 1 and 3 (2 and 4), *Downstream Tariff Exposure*$_{j,T}$ and *Upstream Tariff Exposure*$_{j,T}$ account for include (exclude) the diagonal of the input-output matrix. The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). In columns 1-2 (3-4), the sample includes all manufacturing sectors (all sectors) and covers all executive first terms during 1988-2016. 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-15

The Effects on Trade Protection on Employment Along Supply Chains
(Controlling for Additional Tariffs)

	Manufacturing industries		All industries	
	(1)	(2)	(3)	(4)
Direct Tariff Exposure$_{j,T}$	0.194**	0.221**		
	(0.085)	(0.098)		
Downstream Tariff Exposure$_{j,T}$	-0.971**	-0.908*	-1.359***	-1.372**
	(0.483)	(0.465)	(0.495)	(0.535)
Upstream Tariff Exposure$_{j,T}$	0.571	1.256	0.468	0.193
	(0.461)	(0.982)	(0.469)	(0.551)
$MFN_{j,T}$	-0.002	-0.002		
	(0.003)	(0.002)		
Downstream MFN Exposure$_{j,T}$	-0.004	-0.001	-0.016	-0.010
	(0.008)	(0.006)	(0.015)	(0.011)
Upstream MFN Exposure$_{j,T}$	0.021	0.106	0.016	0.009
	(0.020)	(0.072)	(0.018)	(0.046)
$Retaliation_{j,T}$	0.035	-0.051		
	(0.046)	(0.101)		
Downstream Retaliation Exposure$_{j,T}$	0.005	-0.131	-0.016	0.432
	(0.157)	(0.266)	(0.015)	(0.288)
Upstream Retaliation Exposure$_{j,T}$	-0.368	-0.711	0.016	0.018
	(0.322)	(0.559)	(0.018)	(0.325)
Sector FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,567	1,567	1,915	1,915
KP F-statistic	12.4	4.69	23.4	11.2

Columns 1-2 report 2SLS estimates of equation (11), while columns 3-4 report 2SLS estimates of equation (12). 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 duties and countervailing duties, as measured by equations (1)-(3), instrumented using the corresponding IV variables. In column 1 and 3 (2 and 4), *Downstream Tariff Exposure*$_{j,T}$ and *Upstream Tariff Exposure*$_{j,T}$ include (exclude) the diagonal of the input-output matrix. The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). In columns 1-2 (3-4), the sample includes all manufacturing sectors (all sectors) and covers all executive first terms during 1988-2016. 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.