Trade Protection Along Supply Chains*

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Abstract

We combine detailed information on US temporary trade barriers (antidumping duties, countervailing duties, and safeguards) during 1989-2020 with US input-output data to study the effects of trade protection along supply chains. We focus on measures imposed against China, which has been the main target of US trade protection during the last decades. To deal with endogeneity concerns, we use an instrumental variable strategy, exploiting changes in the identity of swing states across presidential terms and heterogeneous exposure to these political shocks across industries. We find that politically motivated trade protection generates winners and losers: it fosters employment growth in protected industries, but hampers employment growth in downstream industries. Our estimates imply a negative overall impact on US jobs.

JEL Classifications: D72, F13, F16

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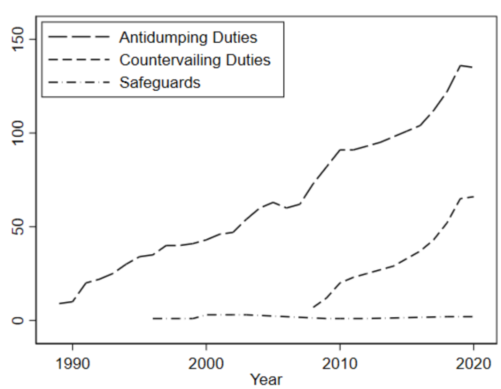
1 Introduction

The last few decades have witnessed the rise of China as a world trading power. Thanks to its deep economic reforms in the 1980s and 1990s and its accession to the World Trade Organization (WTO) in 2001, China went from accounting for around 2% of global manufacturing exports in 1990 to being the largest exporting country in the world. This has stimulated an intense academic and policy debate about the negative effects of rising import competition from China on US employment (e.g., Autor *et al.*, 2013; Acemoglu *et al.*, 2016; Pierce and Schott, 2016).

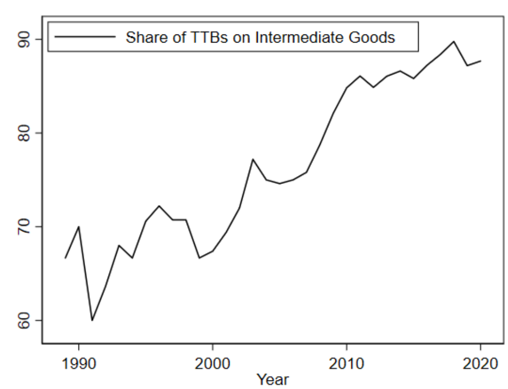
Less attention has been devoted to the effects of protectionist measures imposed on imports from China. Recent studies have examined the effects of the special measures introduced in 2018 by the Trump administration and the resulting retaliation (e.g., Fajgelbaum *et al.*, 2020; Flaaen *et al.*, 2020; Flaaen and Pierce, 2024). However, well before President Donald Trump took office in 2017, the United States had been targeting China through its temporary trade barriers (TTBs): antidumping (AD) duties, countervailing (CV) duties, and safeguards. Unlike most-favored-nation (MFN) tariffs, which are bound to the levels agreed during multilateral negotiations and cannot be applied in a discriminatory manner, TTBs can be used to temporarily increase protection and can be targeted to specific countries.

Figure 1

Temporary Trade Barriers Against China (1989-2020)



(a)



(b)

Panel (a) shows the number of US TTBs (AD duties, CV duties, and safeguards) applied on imports from China. Panel (b) shows the share of US TTBs applied on imports from China of intermediate goods, based on the Broad Economic Categories classification. Authors' calculations based on Bown *et al.* (2020).

Panel (a) of Figure 1 illustrates the rise in the number of TTBs — particularly AD duties — applied by the United States on imports from China during 1989-2020. Panel (b) shows that US TTBs are skewed towards intermediate goods, identified using the Broad Economic Categories classification. In a world in which production processes are fragmented across countries and intermediate goods account for as much as two-thirds of international trade (e.g., Yi, 2003; Johnson and Noguera, 2012; Antràs and Chor, 2022), the effects of trade protection can propagate along supply chains, harming producers in downstream industries.[1] In this paper, we examine the effects of trade protection on employment along supply chains. To this purpose, we combine detailed information on US TTBs during 1989-2020 with US input-output data to identify industries directly and indirectly exposed to trade protection.

As pointed out by Trefler (1993), endogeneity poses a key challenge to identify the impact of trade policies. Protectionist measures can be influenced by unobservables such as negative productivity shocks to domestic producers, making it harder to identify the effects on directly exposed industries. When studying the effects of protection along supply chains, the results might be confounded by omitted variables correlated with both the level of protection in upstream industries and the performance of downstream industries. For example, positive productivity shocks experienced by firms in China (e.g., producers of semiconductors) could benefit US firms in downstream sectors (e.g., producers of electronic devices), allowing them to purchase inputs at lower prices or higher quality. The same shocks could also increase trade protection on Chinese imports, making it easier for US producers petitioning for a TTB to provide evidence of injury. Omitting these productivity shocks would thus work against finding negative effects of TTBs along supply chains.

To address these concerns, we propose an instrumental variable strategy, exploiting the unique system used to elect the executive in the United States. US citizens do not directly choose the president: they express their preference for a candidate from one party; the candidate that wins a majority of votes in a state appoints *all* the "electors" of that state; the electors from the different states form the Electoral College, which chooses the president.[2] The winner-takes-all nature of this electoral system creates incentives for presidential candidates to target "swing" states, in which a small difference in votes can shift all electors from one candidate to the other. There is evidence that swing-state politics affects presidential candidates' campaign visits (Strömberg, 2008), but much less is known about the effects on

[1] For example, the CEO of the Bicycle Corporation of America has complained that tariffs on bike components, steel and aluminium have raised production costs for the company. As a result, "plans to expand BCA are on hold, costing American jobs" ("The Trouble with Putting Tariffs on Chinese Goods," *The Economist*, May 16, 2019).

[2] A majority of 270 out of the 538 current electors is required to elect the president.

policy choices.

Anecdotal evidence suggests that swing-state politics affects the use of TTBs by incumbent presidents. For example, during his first term, President George W. Bush introduced AD duties and safeguards on imports of steel from China and other countries, to gain votes in Ohio and Pennsylvania, which were expected to be swing states in the next presidential elections.[3] As discussed in Section 2, the US president can affect TTBs through various channels: in the case of AD and CV duties, the White House can directly influence the decisions of the Department of Commerce (DOC), which determines whether imports have been "dumped" or subsidized and sets the level of the duty.[4] The DOC is part of the executive branch and its top officials are nominated by the president. In the case of safeguards, the president makes the final decision on the introduction of these measures.

Our shift-share instrument relies on exogenous political shocks driven by changes in the identity of swing states across electoral terms. Our main definition of swing states is based on Strömberg (2008)'s probabilistic voting model.[5] Exposure to political shocks varies across industries, depending on their importance across states (captured by pre-sample employment levels) and vertical linkages between them (captured by pre-sample input-output coefficients). To alleviate concerns about the exclusion restriction, we interact an industry's exposure to political shocks with that industry's historical knowledge of the complex institutional process to petition for TTBs in the United States (captured by the count of pre-sample petitions).[6] This makes our instrument specific to TTBs, and thus unlikely to pick up the effects of other policies that could be affected by swing-state politics.[7]

[3]See "Bush policies follow politics of states needed in 2004" (*USA Today*, June 16, 2002). During the same term, President Bush introduced other protectionist measures, including AD duties targeting imports of furniture from China. Congressman F. James Sensenbrenner Jr. from Wisconsin, a state with a large furniture industry that was expected to be swing in next presidential elections, pointed out that the rise of imports of wooden furniture from China could be one of the biggest issues in the elections for voters in his state (see "China's Furniture Boom Festers in U.S.," *The New York Times*, January 29, 2004).

[4]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).

[5]Our results are robust to using alternative definitions of swing states, including the one used by Conconi *et al*. (2017) based on the vote shares of Democratic and Republican candidates in the previous elections.

[6]Blonigen and Park (2004) and Blonigen (2006) emphasize the legal and institutional complexity of the petitioning process. The petitioning party must present substantial information to support the case, as well as legal analysis and arguments. As a result, industries with prior petitioning experience face higher probability of success in new cases.

[7]In all regressions, we control for the industry's (not interacted) exposure to swing state politics. Re-election motives could lead the president to manipulate other policies — in particular federal subsidies — to favor key industries in swing states. It should be stressed that federal subsidies require legislation from Congress, which makes it harder for the president to manipulate them for re-election purposes. As discussed in Section 2, the executive can instead directly influence the administration of US TTBs.

We focus on TTBs against China, which has been by far the biggest target of US protection during our sample period.[8] Moreover, our instrumental variable strategy relies on TTBs being responsive to domestic political pressure. Measures against China should be more responsive to such pressure for two reasons: first, China is perceived by US voters as the main threat to US jobs;[9] second, measures against China can more easily be manipulated for political purposes due to its non-market economy status.[10]

We show that the instrument is a strong predictor of trade protection granted to an industry during executive first terms, when the president can be re-elected. The instrument has instead no predictive power during executive second terms, when the president is a lame duck. These findings are consistent with the theoretical model of Conconi *et al.* (2017), in which re-election motives can drive the incumbent executive to use trade policy to favor key industries in swing states. Placebo tests show that using information on states expected to be swing in a given term is key to predict trade protection in that term.

We use our instrument to identify the effects of politically motivated trade protection on directly and indirectly exposed industries. We estimate the employment effects of TTBs during the two-term presidencies of Bill Clinton, George W. Bush, and Barack Obama.[11] We show that politically motivated trade protection generates winners and losers along supply chains: on the one hand, it fosters employment growth in the protected industries; on the other hand, it deters employment growth in downstream industries that use the protected products as inputs. For example, TTBs on imports of steel can foster employment growth in this industry, but can increase production costs in downstream manufacturing (e.g., motor vehicles) and non-manufacturing (e.g., construction) industries, hampering their growth.

We use the methodology of Acemoglu *et al.* (2016) to compute the counterfactual jobs gained and lost due to TTBs. When considering manufacturing industries, our two-stage least squares (2SLS) estimates imply around 177,000 net job losses caused by politically motivated trade protection during 1993-2016, corresponding to 7,500 net job losses per year. These findings resonate with Flaaen and Pierce (2024), who find that the tariffs introduced under President Trump led to net job losses in manufacturing. When extending the analysis

[8]Over the entire 1989-2020 period, 55% of the measures were against China. Since its accession to the WTO in 2001, around 70% of US TTBs targeted China.

[9]As documented by Alfaro *et al.* (2023), "concerns over the role of China as a major US trading partner and the associated concerns about jobs loom large as priors in the minds of the American public."

[10]For example, the US Department of Commerce can employ more flexible methods in AD cases against China, using price and cost information from surrogate countries to compute dumping margins. We show that our instrument has a weaker predictive power when considering TTBs imposed on all target countries.

[11]By focusing on this period, we can compare the effects of politically motivated protection during first term and over the entire presidency. The period also excludes the unprecedented trade protection measures imposed during the first term of President Trump, which triggered the ongoing trade war with China.

to all sectors in the economy, the net job losses increase to 1.1 million, corresponding to around 46,000 net job losses per year.

Our identification strategy relies on exogenous political shocks driven by changes in the identity of swing states across electoral terms.[12] As pointed out by Borusyak and Hull (2023), even if the shocks are randomly assigned, 2SLS estimates may suffer from an omitted variable bias if exposure to the shocks is not random. In our setting, this could arise if heterogeneous exposure of industries to the political shocks — captured by their geographical distribution across states and their historical experience at petitioning for TTBs — is correlated with unobservable drivers of employment growth. To address this concern, we show that our results are unaffected if we apply the "recentering" procedure proposed by Borusyak and Hull (2023), by considering counterfactual shocks generated by randomizing the identity of swing states. The results also continue to hold in a series of additional checks (e.g., using alternative measures of trade protection, alternative definitions of swing states, including additional controls).

Our paper contributes to three main streams of literature. The first is the large literature on TTBs, which is mostly focused on AD duties (see Blonigen and Prusa, 2016 for a review).[13] To address concerns about the endogeneity of trade protection, some authors combine a difference-in-differences methodology with propensity score matching (Konings and Vandenbussche, 2008; Pierce, 2011). Ours is the first paper to propose an instrument for TTBs to study their causal effects along supply chains.

We also build on the literature on the political economy of US trade policy. Several papers study the political economy of trade liberalization votes in the US Congress (e.g., Conconi *et al.* 2012 and 2014; Blanga-Gubbay *et al.*, 2025). Others focus on US AD duties (e.g., Finger *et al.*, 1982; Moore, 1992; Hansen and Prusa, 1997; Aquilante, 2018). A few studies document a swing-state bias in the coverage of non-tariff barriers under President Reagan (Muûls and Petropoulou, 2013), in US trade disputes (Conconi *et al.*, 2017), US MFN tariffs in 1996 (Ma and McLaren, 2018), and the tariffs introduced by President Trump in his first term (Fajgelbaum *et al.*, 2020). Ours is the first paper to systematically show that swing-

[12] We show that the identity of swing states is uncorrelated with state-level characteristics (e.g., previous exposure to import competition, the importance of the manufacturing sector, and the extent to which it has been declining). We also show that whether a state is classified as swing is uncorrelated with the previous level of trade protection granted to industries in that state.

[13] Some studies examine their determinants (e.g., Finger *et al.*, 1982; Bown and Crowley, 2013). Others examine their trade destruction effects on imports from targeted countries (e.g., Prusa, 2001; Lu *et al.*, 2013; Besedes and Prusa, 2017), or the indirect effects on third countries (e.g., Prusa, 1997; Bown and Crowley, 2007; Vandenbussche and Zanardi, 2010). A few studies examine their effects on welfare (Gallaway *et al.*, 1999) and FDI (Blonigen, 2002).

state politics affects US protectionist measures (AD duties, CV duties, and safeguards) and to study the effects of politically motivated protection along supply chains.

Finally, our paper contributes to the literature on trade protection and input-output linkages. Various studies have emphasized the productivity-enhancing effects of input liberalization (e.g., Amiti and Konings, 2007; Goldberg *et al.*, 2010; Halpern *et al.*, 2015). Others have examined the effects of trade policy along value chains (e.g., Yi, 2003; Erbahar and Zi, 2017; Conconi *et al.*, 2018, Blanchard *et al.*, 2025). Our findings are in line with previous theoretical and empirical studies that document the detrimental effects of TTBs. Blonigen (2016) shows that protecting steel imports is harmful to downstream sectors. Barattieri and Cacciatore (2023) estimate the dynamic employment effects of AD duties, and find that these measures have small beneficial effects in protected industries, but negative effects on downstream industries. Cox (2023) finds that the Bush steel tariffs in 2002-2003 had a persistent negative effect on steel-using industries in the US. Finally, echoing our findings, de Souza and Li (2025) use a difference-in-differences methodology and show that AD duties in Brazil increased employment in protected sectors at the expense of employment in downstream industries. We contribute to this literature by studying the causal effects of politically motivated trade protection on employment along supply chains.

The rest of the paper is structured as follows. Section 2 provides information on the administration of TTBs in the United States. Section 3 describes the data and variables used in our empirical analysis. Section 4 explains our identification strategy. Section 5 presents the empirical results. Section 6 concludes.

2 The Administration of TTBs in the United States

Multilateral trade rules allow WTO members to use three types of contingent protectionist measures: AD duties, CV duties, and safeguards. In this section, we briefly describe the institutional process through which these measures are administered in the United States.

2.1 AD Duties

Antidumping (AD) is the most frequently used form of TTB. 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. While

AD duties are designed to defend producers against "unfair" import competition, they have been described as "simply a modern form of protection" (Blonigen and Prusa, 2003).

In the United States, AD is managed by two agencies, each with different competencies: the US Department of Commerce (DOC),[14] which is in charge of the dumping investigation, and the US International Trade Commission (ITC), which is in charge of the injury investigation. As mentioned in the introduction, the DOC is an integral part of the US Administration. The president nominates its top officials and can directly influence its decisions. Instead, the ITC is a bipartisan agency composed of six commissioners nominated by the President (with no more than three commissioners from the same party). Previous studies show that ITC commissioners are subject to political pressure (e.g., Moore, 1992; Hansen and Prusa, 1997; Aquilante, 2018).

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. 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 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 often relies on surrogate countries to determine the dumping margin.

The ITC is in charge of the injury investigation, i.e., "determine[s] whether a US industry is materially injured or is threatened with material injury, or whether the establishment of

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

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

an industry is materially retarded" due to dumped imports (see https://www.usitc.gov/investigations/import_injury). If the ITC investigation is affirmative, an AD duty equal to the dumping margin established by the DOC is introduced.

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 Sunset Reviews. Bown *et al.* (2021) document that US AD duties are usually extended and last on average for 12 years.

2.2 Countervailing Duties

The WTO Agreement on Subsidies and Countervailing Measures sets forth rules and procedures to govern the application of a countervailing (CV) duty which is used to counter the negative effects of subsidized exports. The procedure for the introduction of CV duties is very similar to that used for AD duties: the DOC investigates whether an actionable subsidy is being provided and the ITC examines whether a domestic industry is being injured by subsidized exports. CV duties are less frequently used than AD duties (see panel (a) of Figure 1) and are often simultaneously imposed with AD measures on the same targeted product-country.[16]

2.3 Safeguards

Finally, the United States implements measures to address import relief (or safeguard actions) in accordance with GATT Article XIX and the WTO Safeguards Agreement. Although they are more rarely used than AD duties, they cover a larger share of US imports since they target all countries (with few exceptions).[17] The procedure for the introduction of safeguards starts with the receipt of a safeguard petition. The ITC then assesses whether imports of the applicable products are, or threaten to be, a substantial cause of disruption to the domestic industry. If a positive determination is made, the ITC makes recommendations to the President and to the Office of the United States Trade Representative (USTR), a part of the Executive Office of the President, on the type of remedy that would provide for import relief. The president makes the final decision on whether to introduce a safeguard and on the level of the tariff.

[16] In 1989-2020, 91% of CV measures had a corresponding AD measure. In our analysis, we only count the stand-alone CV duties (two against China) as additional measures.

[17] In 1989-2020, the US imposed 8 global safeguard measures under Section 201 of the US Trade Act of 1974, and one China-specific safeguard measure under Section 421 of the US Trade Act of 1974.

3 Data and Variables

3.1 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). We map product-level TTBs to sectors, defined as 4-digit codes in the Standard Industrial Classification (SIC4).[18] Appendix A.1 details our matching procedure to link each investigation to a corresponding industry code.

As mentioned in the introduction, our empirical analysis focuses on TTBs introduced by the United States against China, which is by far the most frequent target of US trade protection in our sample period. Moreover, TTBs against China are more likely to be shaped by domestic politics, given that US voters perceive China as a major threat in international trade (Alfaro *et al.*, 2023), and that measures against China can more easily be manipulated for political purposes due to its non-market economy status.

To capture protection granted to SIC4 industry j during presidential term T, we define the variable $\textit{Trade Protection}_{j,T}$. In our baseline specification, this is a dummy variable equal to 1 if HS6 products within industry j are subject to TTBs during term T. In robustness checks, we use two alternative measures: the share of HS6 products within industry j subject to TTBs; and an indicator variable for whether products in sector j are subject to AD duties only (the most commonly used TTB). Note that within an industry j, variation in $\textit{Trade Protection}_{j,T}$ across electoral terms comes from the imposition of new measures and the revocation or renewal of old measures via Sunset Reviews.

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 close to the beginning of our sample period.[19]

[18] We use "sectors" and "industries" interchangeably when referring to SIC4 codes.

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

We convert 6-digit BEA industry codes into SIC4 codes 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 a major reason why they have been used to capture technological linkages between sectors, even in cross-country studies (e.g., Acemoglu *et al.*, 2009; 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 crucial role in the US economy. Notice that steel (SIC 3312) is the most important input for 84 industries (see Table A-2) and is also one of the primary recipients of TTBs (see Table A-4).

Combining information on US TTBs with the 1992 US input-output table, we construct measures of direct and indirect exposure to trade protection along supply chains.[20] An industry's direct tariff exposure is captured by the presence of TTBs in that industry:

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

where $Trade\ Protection_{j,T(P)}$ is a dummy variable equal to 1 if HS6 products within industry j are subject to TTBs in term T (during presidency P) or one of the alternative TTB measures.

When studying the indirect effects of TTBs along supply chains, we follow Acemoglu *et al.* (2016) in using "downstream exposure" to capture the effects that propagate downstream (i.e., from an industry to its customers) and "upstream exposure" to capture the effects that propagate upstream (from an industry to its suppliers).[21] The effects of trade protection on downstream industries are thus given by:

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

where $\omega_{i,j}$ is the cost share of input i in the production of j. This variable captures exposure to TTBs that protect j's input industries. Similarly, the effects of trade protection on

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

[21]As pointed out by Acemoglu *et al.* (2016), "the terminology of upstream and downstream effects is open to confusion, since upstream effects – i.e., effects that propagate upstream—work through the import exposure experienced by downstream industries, and similarly for downstream effects" (p. 148).

upstream industries are given by:

$$Upstream\ Tariff\ Exposure_{j,T(P)} = \sum_{i=1}^{N} \theta_{j,i}\, Trade\ Protection_{i,T(P)}, \tag{3}$$

where $\theta_{j,i}$ is the share of industry j's total sales that are used as inputs in the production of industry i. This variable captures exposure to TTBs that protect j's customers. To obtain $\omega_{i,j}$ and $\theta_{j,i}$, we use the Leontief inverse of the input-output matrix to take into account direct and indirect (higher-order) linkages. When constructing the variables *Downstream Tariff Exposure*$_{j,T(P)}$ and *Upstream Tariff Exposure*$_{j,T(P)}$, we include the diagonal of the input-output matrix ($\omega_{j,j}$ and $\theta_{j,j}$) to allow for vertical linkages within SIC4 industries.[22] Table A-3 reports descriptive statistics of the exposure variables.

3.2 Swing States

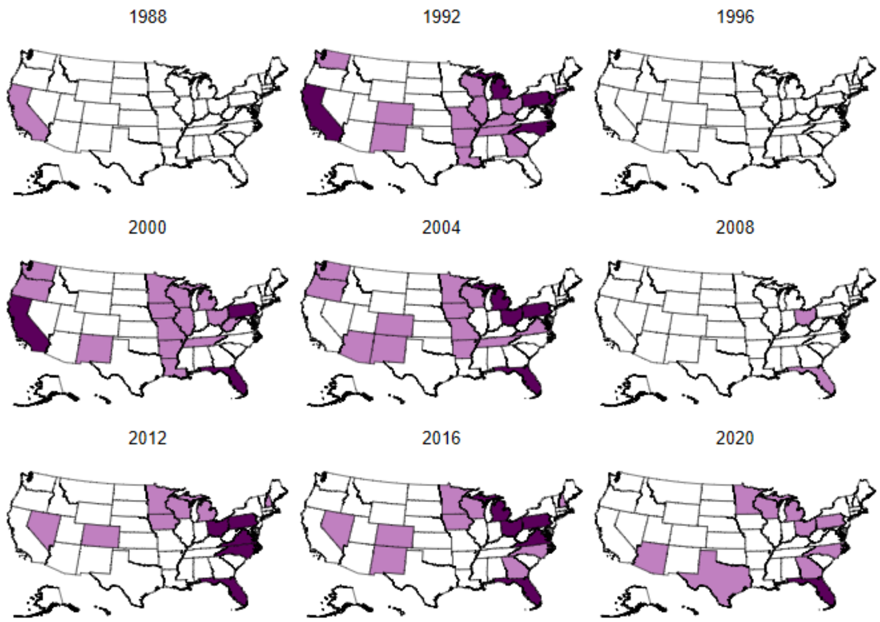
Our main definition of swing states is grounded in Strömberg (2008)'s probabilistic-voting model of political competition under the Electoral College. In this model, electoral outcomes are uncertain, due to national and state-specific shocks.[23] The model can explicitly be solved and directly estimated using a set of observables to derive the variable *Swing State*$_{s,T(P)}$, i.e., the probability that state s is a "decisive swing state" in the presidential elections at the end of term T (during presidency P). This is the joint probability that, ex post facto, state s is (i) a swing state, in the sense that the state-level outcome is very close, and (ii) decisive, in the sense that winning the state is necessary to obtaining a majority in the Electoral College and thus winning the election. David Strömberg kindly provided us with the estimates of this variable for our sample period.[24]

[22] In robustness checks, we exclude the diagonal when constructing the indirect tariff exposure variables.

[23] As an example of national shocks, Strömberg mentions the US government's attempt to rescue hostages in Iran in 1980, which ended in a helicopter crash that killed eight servicemen and led to a drastic fall in support for President Carter across the US. An example of state-level shocks is the unexpected downturn in a state's economy, which may shift voters' preferences for government spending and unemployment insurance.

[24] As discussed in Section II of Strömberg (2008), estimation amounts to predicting state-level Democratic vote shares using a set of observables, and then estimating national and state-level uncertainty in this prediction. The estimation is based on a wide range of nationwide variables (e.g., Democratic vote share of the two-party vote share in trial-heat polls from mid-September, lagged Democratic vote share of the two-party vote share, second-quarter economic growth, an indicator for whether the incumbent president is running for reelection) and statewide variables (lagged and twice lagged difference from the national mean of the Democratic two-party vote share, first-quarter state economic growth, average ADA-scores of each state's members of Congress in the year before the election, the Democratic vote-share of the two-party vote in the midterm state legislative election, an indicator for the home state of the president).

Figure 2
Swing States in Presidential Elections



The figure illustrates the states with the highest probability of being decisive swing states in the presidential elections covering the 1988-2020 period, based on Strömberg (2008)'s probabilistic voting model. States above the 95^{th} percentile (between the 80^{th} and 95^{th} percentile) of the distribution of $Swing\ State_{s,T(P)}$ are highlighted in dark purple (purple).

Figure 2 shows the states with the highest probability of being decisive in US presidential elections between 1988 and 2020, specifically those above the 80th percentile of the distribution of $Swing\ State_{s,T(P)}$. States are colored in light purple if they fall between the 80th and 95th percentiles, and in dark purple if they are above the 95th percentile. Two main patterns emerge. First, pivot probabilities vary markedly across election cycles: in close races like 2000, 2004, and 2016, decisiveness spreads across several states, while in less competitive contests, probabilities are uniformly low. For example, in 1996, when Clinton won by a wide margin (379-159 electoral votes), most states showed negligible probabilities of being pivotal. Similarly, in 1988's Bush-Dukakis contest, only California had a (low) positive probability of being decisive, probability due to its large electoral weight.[25] Second, there is substantial heterogeneity across states: smaller states like Delaware consistently show near-zero probabilities, while others like Ohio and Florida repeatedly rank among the most decisive, appearing above the 95th percentile in five of the nine elections due to their size and competitiveness.

Our identification strategy relies on exogenous changes in the identity of swing states

[25]The number of electoral votes is proportional to a state's population. In 1988, it ranged from 3 (Alaska, Delaware, District of Columbia, North Dakota, South Dakota, Vermont, and Wyoming) to 47 (California).

across elections. In Section A-2 of the Appendix, we verify that the variable $\textit{Swing State}_{s,T(P)}$ is uncorrelated with various state-level characteristics (e.g., previous exposure to import competition, the size of the manufacturing sector and the extent to which it has been declining) and with the extent to which its industries have been protected during that term (see Table A-1).

In our main analysis, we use the continuous version of the variable $\textit{Swing State}_{s,T(P)}$ based on Strömberg's model. In robustness checks, we use alternative dichotomous definitions of swing states based on: the difference in vote shares between the Democratic and Republican candidates in the previous presidential elections, the Electoral College ratings of the Cook Political Report (CPR), and Gallup polls. In these robustness checks, $\textit{Swing State}_{s,T(P)}$ is an indicator variable equal to 1 if the vote margin between the candidates of the two parties in the next presidential election is expected to be small in state s (see Section 4.2 for details).

3.3 Importance of Industries in Swing States

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

$$\textit{Swing Industry}_{j,T(P)} = \frac{\sum_s L_{s,j} \times \textit{Swing State}_{s,T(P)}}{\sum_{s,j} L_{s,j} \times \textit{Swing State}_{s,T(P)}}, \tag{4}$$

where $L_{s,j}$ measures employment of industry j in state s, constructed using pre-sample (1988) data from County Business Patterns.[26] As discussed above, the variable $\textit{Swing State}_{s,T(P)}$ captures the probability that state s is a decisive swing state in the next presidential elections, based on Strömberg (2008)'s probabilistic voting model. $\textit{Swing Industry}_{j,T(P)}$ is thus the ratio of total employment in manufacturing industry j in states expected to be swing in the elections at the end of term T, over total manufacturing employment in those states.

Notice that, within a SIC4 industry j, variation in $\textit{Swing Industry}_{j,T(P)}$ comes from changes in the identity of swing states across electoral terms (captured by the variable $\textit{Swing State}_{s,T(P)}$). Within a term T, cross-industry variation comes from differences in the importance of industries across states (captured by the pre-sample employment levels $L_{s,j}$).

Descriptive statistics of the variable $\textit{Swing Industry}_{j,T(P)}$ 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

[26] We use pre-sample data to alleviate endogenity concerns regarding the effect of trade protection on future employment levels. Using time-varying employment data would yield very similar results, given that the geographical distribution of industries across states is very stable over time: the correlation between labor shares constructed at the start and end of our sample is 0.9 (see Figure A-2).

Swing Industry$_{j,T(P)}$ during 1989-2020, including highly protected sectors such as "Motor vehicle parts and accessories" (SIC 3714), "Blast furnaces and steel mills" (SIC 3312), and "Furniture and fixtures, n.e.c." (SIC 2599).

3.4 Petitioning Experience

We also exploit heterogeneous ability of industries to obtain trade protection. As discussed in Section 2, the introduction of TTBs requires an initial petition from representatives of the industry (i.e., large individual firms and/or industry associations) that is injured or threatened to be injured by imports. Focusing on AD duties — the most frequently used TTB — Blonigen (2006) points out that the petitioning process is extremely complex (see also footnote 15). As a result, petitioners with prior experience are more effective in arguing their case, which increases the probability of a favorable outcome. Building on these arguments, we construct the variable $Experience_j$, which is the count of AD petitions filed by industry j before the start of our sample period. We include all petitions between 1980 (the first year for which the data is available) and 1987 (the year before the first presidential election in our sample period).

As pointed out by Irwin (2005), during the 1980s, legal and institutional changes made it easier to file for AD protection, leading to a steep increase in the number of AD petitions. However, some industries did not need to petition, since they were already protected by other policies (e.g., voluntary export restraints or quotas): the experience variable is thus positive for only 45% of manufacturing industries.[27] Descriptive statistics of the variable $Experience_j$ are reported in Table A-3. The bottom panel of Table A-4 lists the top-10 SIC4 sectors by number of pre-sample petitions.

4 Identification Strategy

The main goal of our paper is to study the distributional employment effects of politically motivated trade protection. Using OLS would produce biased estimates largely due to omitted (unobserved) variables. For example, positive productivity shocks to foreign exporters,

[27]In line with Blonigen (2006), the number of petitions filed by an industry depends crucially on its previous experience: the correlation between the number of petitions filed by SIC4 industry j during our sample period and $Experience_j$ is 0.86, significant at the 1% level. Blonigen finds that prior AD experience is also associated with lower dumping margins and interprets this result as suggesting that experience lowers filing costs, leading to the filing of weaker cases. In our sample period, we find instead that the correlation between $Experience_j$ and the average dumping margin of cases filed by industry j is positive (0.20) and significant at the 1% level.

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 TTBs 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 TTB 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 (in absolute value), working against finding adverse effects of trade protection on downstream industries.

4.1 An Instrument for Politically Motivated Trade Protection

To identify causal effects, we construct a (non-linear) shift-share instrument that captures the impact of shocks (or "shifters") on units with varying exposure, measured using a set of disaggregated weights (or "shares"). In our setting, the shifters are political state-level shocks and the shares capture heterogeneous industry exposure to these shocks.

To predict the level of protection granted to industry j during term T, we construct our instrument as the interaction between the industry's (time-varying) importance in swing states (captured by $\textit{Swing Industry}_{j,T(P)}$), and its (time-invariant) historical petitioning experience (captured by $\textit{Experience}_j$):

$$IV_{j,T(P)} = \textit{Swing Industry}_{j,T(P)} \times \textit{Experience}_j. \tag{5}$$

An alternative strategy would be to simply use the variable $\textit{Swing Industry}_{j,T(P)}$ as the instrument. However, by itself, this variable 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. Interacting $\textit{Swing Industry}_{j,T(P)}$ with $\textit{Experience}_j$ makes the instrument TTB-specific, alleviating concerns about the exclusion restriction: $IV_{j,T(P)}$ takes into account the importance of an industry in swing states only to the extent that the industry has some petitioning experience. To account for the role of other policies, we control for $\textit{Swing Industry}_{j,T(P)}$ by itself in all regressions.

The logic behind our instrument is that trade 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 TTBs. In line with this idea, Table A-4 shows that 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 petitioning experience, are among the most protected. By contrast, sectors such as "Newspapers" (SIC 2711) and "Search and navigation equipment" (SIC 3812), which score highly in terms of average $Swing\ Industry_{j,T(P)}$ but have no historical petitioning experience, receive no trade protection.

4.2 Predicting Trade Protection

Our empirical strategy is guided by the theoretical model of Conconi *et al.* (2017), in which voters have reciprocal preferences, i.e., want to reward politicians who have been kind to them and punish those who have been unkind. Crucially, if voters were fully rational (i.e., in the absence reciprocity), their decisions would not depend on past policy choices and swing-state politics would have no impact on trade policy. The model demonstrates that the incumbent's ability to set trade policy provides an advantage over the challenger, who cannot commit to trade policy before being elected. The model yields two key implications: first, the incumbent executive has incentives to manipulate trade policy in favor of key industries in swing states (those in which voters' ideological preferences are not too strong); second, swing-state politics should only affect trade protection during first terms, when the president can be re-elected.[28]

To assess the validity of these predictions, we estimate the following regression separately for executive first and second terms:

$$Trade\ Protection_{j,T(P)} = \beta_0 + \beta_1 IV_{j,T(P)} + \beta_2 Swing\ Industry_{j,T(P)} + \delta_j + \delta_{T(P)} + \varepsilon_{j,T(P)}. \quad (6)$$

The inclusion of sector fixed effects at the SIC4 level (δ_j) allows us to control for any time-invariant characteristic of a SIC4 industry, including $Experience_j$. Term fixed effects ($\delta_{T(P)}$) account for time-varying macroeconomic and political conditions. In line with earlier studies (e.g., Pierce and Schott, 2016), we weight regression estimates by pre-sample (1988) industry employment to account for heterogeneity in the size of the 392 manufacturing SIC4 industries.

[28]Second-term effects are theoretically possible, if voters behave reciprocally towards the incumbent's party rather than the incumbent president.

We cluster standard errors at the SIC3 level (135 manufacturing industries) to allow for correlated industry shocks.

Table 1

IV and Trade Protection (First and Second Terms)

	First Terms (1)	Second Terms (2)	First Terms (3)	Second Terms (4)
$IV_{j,T(P)}$	1.663***	-0.259		
	(0.467)	(0.221)		
Swing Industry$_{j,T(P)}$	10.545*	-1.060	20.626***	-2.655
	(6.008)	(5.778)	(7.293)	(4.985)
Sector FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.54	0.56	0.53	0.56
Observations	1,960	1,176	1,960	1,176

The dependent variable is *Trade Protection*$_{j,T(P)}$, a dummy variable equal to 1 if any product in industry j is subject to TTB measures during term T (of presidency P). $IV_{j,T(P)}$ is defined in equation (5), while *Swing Industry*$_{j,T(P)}$ is defined in equation (4). These variables are constructed using *Swing State*$_{s,T(P)}$, the probability that state s is a decisive swing state in the next presidential elections, based on Strömberg (2008)'s probabilistic voting model. In columns 1 and 2 (3 and 4), the sample covers all executive first terms (second terms) during the 1989-2020 period. 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.

Columns 1 and 2 of Table 1 report OLS estimates of equation (6) for executive first and second terms, respectively. The positive and significant coefficient of $IV_{j,T(P)}$ in column 1 indicates that our instrument is a strong predictor of trade protection during first terms, when the president can be re-elected. In terms of magnitude, a percentage point increase in $IV_{j,T(P)}$ increases the probability of protection by about 1.7 percentage points, equivalent to 12% of the mean probability of protection (14%). The coefficient of *Swing Industry*$_{j,T(P)}$ is also positive and significant in column 1, indicating that swing-state politics affects US trade protection during first terms, even in industries with no petitioning experience. The coefficients of $IV_{j,T(P)}$ and *Swing Industry*$_{j,T(P)}$ are instead not statistically significant in column 2, indicating that swing-state politics has no impact on trade protection when the president cannot be re-elected. Columns 3 and 4 include only *Swing Industry*$_{j,T(P)}$ and confirm that US TTBs increase with the importance of industries in states expected to be swing, but only during executive first terms.

Given the aggregate negative effects of TTBs on employment in downstream industries documented in Section 5, one may be concerned that equation (6) does not account for the political importance of downstream industries. If we further include a variable capturing the size of downstream industries in swing states, the coefficient of this variable is negative but not significant (and the coefficient of $IV_{j,T(P)}$ is statistically unaffected).[29] This result may partly be explained by the fact that final good industries tend to be more geographically dispersed than input industries, implying that employment losses in downstream industries may be less salient than employment gains in protected industries.[30]

The results of Table 1 show that our instrument is a strong predictor of protection granted to an industry during executive first terms, when the president has re-election motives. The causal interpretation of these findings requires that trade protection does not affect the identity of states expected to be swing. The evidence presented in Section A-2 of the Appendix shows that the probability that a state is a decisive swing state in the presidential elections at the end of a term is uncorrelated with the extent to which its industries have been protected during that term (see Table A-1).

In Table 2, we use alternative definitions of swing states to construct $\textit{Swing Industry}_{j,T(P)}$ and $IV_{j,T(P)}$. Column 1 reproduces our main specification based on Strömberg (2008)'s model (corresponding to column 1 in Table 1). In all other specifications, $\textit{Swing State}_{s,T(P)}$ is an indicator variable equal to 1 if the vote margin between the candidates of the two parties in the next presidential election is expected to be small. In column 2, a state s is classified to be swing in term T if the vote margin between the candidates in the previous presidential elections was less than 5% (as in Conconi *et al.*, 2017). In columns 3 and 4, we modify this threshold to 4% and 6% respectively. In column 5, we classify swing states based on the Electoral College Ratings the Cook Political Report (CPR).[31] Finally, in column 6 we use data on Gallup polls to identify states expected to be swing in the next presidential elections.[32] In all specifications, the coefficient of $IV_{j,T(P)}$ remains positive and significant, confirming that our instrument is a strong predictor of TTBs during executive first terms, when the incumbent president can be re-elected.[33]

[29]To capture the political importance of downstream industries, we construct $\textit{Downstream Industry Exposure}_{j,T(P)}$. The denominator of this variable is the same as in equation (4), but includes all industries, not just manufacturing. The numerator is $\sum_{s,i} \omega_{j,i} L_{s,i} \times \textit{Swing State}_{s,T(P)}$, where $\omega_{j,i}$ is the cost share of manufacturing industry j in the production of industry i.

[30]The correlation between the measure of industry "upstreamness" developed by Antràs *et al.* (2012) and the index of industry spatial concentration of Ellison and Glaeser (1997) is 0.24 (significant at the 1% level). This point is illustrated by Figure A-3 in the Appendix, which shows the geographical distribution across US states of two industries: SIC 3312 ("Blast furnaces and steel mills") and SIC 1510 ("Construction").

[31]These ratings assess the competitiveness of the states in the Electoral College, based on several factors (e.g., the state and district's political makeup, the political environment in the state and nationally, interviews with campaign professionals). We use the "toss-up" classification to identify swing states.

[32]A state is coded as swing if the predicted vote margin between the top two candidates is less than 5%.

[33]When we reproduce Table 2 for second terms, the coefficient of $IV_{j,T(P)}$ is never statistically significant.

Table 2
IV and Trade Protection (First Terms),
Alternative Definitions of Swing States

	Baseline	5%	4%	6%	CPR	Gallup
	(1)	(2)	(3)	(4)	(5)	(6)
$IV_{j,T(P)}$	1.663***	1.202***	1.639*	1.505***	0.500***	1.022***
	(0.467)	(0.325)	(0.885)	(0.533)	(0.191)	(0.154)
$\textit{Swing Industry}_{j,T(P)}$	10.545*	2.014	1.494	2.650	0.128	0.777
	(6.008)	(6.586)	(6.673)	(5.565)	(8.913)	(7.452)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.54	0.55	0.54	0.55	0.53	0.54
Observations	1,960	1,960	1,960	1,960	1,960	1,960

The table reports OLS estimates of equation (6). The dependent variable is $\textit{Trade Protection}_{j,T(P)}$, a dummy variable equal to 1 if any product in industry j is subject to TTB measures during term T (of presidency P). $IV_{j,T(P)}$ is defined in equation (5), while $\textit{Swing Industry}_{j,T(P)}$ is defined in equation (4). These variables are constructed using alternative versions of the variable $\textit{Swing State}_{s,T(P)}$, which captures states expected to be swing in the presidential elections at the end of term T. In the baseline specification of column 1, this is the probability that state s is a decisive swing state in the next presidential elections, based on Strömberg (2008)'s probabilistic voting model. In all other specifications, $\textit{Swing State}_{s,T(P)}$ is an indicator variable equal to 1 is the vote margin between the candidates of the two parties in the next presidential election is expected to be small: in columns 2-4, a state is classified as swing if the vote margin between the candidates in the previous presidential elections was smaller than a threshold (respectively of 5%, 4%, and 6%); in columns 5 and 6, we respectively use ratings from the Cook Political Report and poll data from Gallup to define states expected to be swing in the next presidential elections. The sample covers all executive first terms during 1989-2020. Observations are weighted by 1988 employment. Sector fixed effects are defined at the SIC4 level. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

In Table 3, we use alternative measures of trade protection and samples. In column 1, the variable $\textit{Trade Protection}_{j,T(P)}$ is the share of HS6 products within SIC4 industry j that are covered by TTBs in term T (during presidency P). In column 2, it is an indicator variable for whether products within the industry are covered by AD duties, the most widely used TTB. In the remaining columns, we use the baseline measure of trade protection, but modify the sample. In column 3, we exclude the steel industry (SIC 3312), which has the highest number of pre-sample petitions. In columns 4 and 5, we respectively exclude the first terms of President Bush Sr. and President Trump, who did not get re-elected at the end of their first terms. In all specifications, the coefficient of $IV_{j,T(P)}$ remains positive and significant. Finally, in column 6 we consider TTBs against all target countries, rather than restricting the analysis to measures targeting China. The coefficient of $IV_{j,T(P)}$ is much smaller than in our baseline specification, in line with our argument that TTBs against China should be more responsive to swing-state politics.

Table 3
IV and Trade Protection (First Terms),
Alternative TTB Measures and Samples

	Product Share (1)	AD Only (2)	No Steel (3)	No Bush (4)	No Trump (5)	All Countries (6)
$IV_{j,T(P)}$	0.242***	1.731***	4.458***	1.310**	2.423***	0.742**
	(0.037)	(0.489)	(0.989)	(0.551)	(0.450)	(0.294)
$\textit{Swing Industry}_{j,T(P)}$	0.705	9.891	0.906	8.145	14.684**	-11.178
	(1.751)	(6.321)	(8.521)	(6.377)	(6.170)	(7.682)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.50	0.56	0.54	0.56	0.54	0.56
Observations	1,960	1,960	1,955	1,568	1,568	1,960

The table reports OLS estimates of equation (6). In column 1, $\textit{Trade Protection}_{j,T(P)}$ measures the share of products in industry j that are covered by TTBs during term T; in column 2, it is a dummy variable equal to 1 if any product in industry j is subject to AD duties during term T; in all other columns, it is a dummy variable equal to 1 if any product in industry j is subject to TTB measures during term T. $IV_{j,T(P)}$ is defined in equation (5), while $\textit{Swing Industry}_{j,T(P)}$ is defined in equation (4). These variables are constructed using $\textit{Swing State}_{s,T(P)}$, the probability that state s is a decisive swing state in the next presidential elections, based on Strömberg (2008)'s probabilistic voting model. The sample covers all executive first terms during 1989-2020 (except in columns 4 and 5, which respectively exclude the first terms of President Bush Sr. and President Trump); it includes all manufacturing industries, apart from column 3, which excludes the steel industry; it covers TTBs against China (except in column 6, which includes TTBs against all target countries). 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 have also carried out a series of additional robustness checks. The coefficient of $IV_{j,T(P)}$ remains positive and significant if we: drop one industry at a time; drop one term at a time; include non-manufacturing industries in the denominator of $\textit{Swing Industry}_{j,T(P)}$; control for lagged $IV_{j,T(P)}$ and $\textit{Swing Industry}_{j,T(P)}$; control for lagged trade protection; control for the size of the industry (based on total US employment) and its lobbying power (based on information on lobbying expenditures available under the Lobbying Disclosure Act). These results are available upon request.

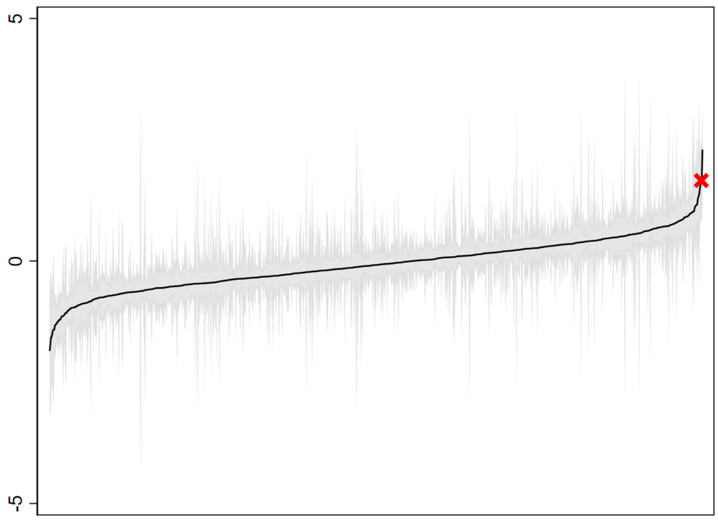
4.3 Placebo Tests

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 actual states expected to be swing in a given term is key to predicting trade protection in that term. To this purpose, we carry out placebo tests, randomizing the identity of swing states used to construct our instrument.

For each state s, we randomly reassign its swing state values across the nine presidential elections between 1988 and 2020. We perform 1,000 such randomizations, constructing the associated *Placebo Swing State*$_{s,T(P)}$ and *Placebo IV*$_{s,T(P)}$ in each iteration. The final placebo instruments are defined as the average values across all random draws.

Figure 3

Estimated Coefficients of *Placebo IV*$_{j,T(P)}$



The figure plots the β_1 coefficients (with 99% confidence intervals) obtained from 1,000 randomizations of *Swing State*$_{s,T(P)}$, generating *Placebo IV*$_{j,T(P)}$. The red cross corresponds to the estimated coefficient of $IV_{j,T(P)}$ in column 1 of Table 2 (1.663).

To carry out the placebo tests, we re-estimate (6) on executive first terms, but replace $IV_{j,T(P)}$ and *Swing Industry*$_{j,T(P)}$ with *Placebo IV*$_{j,T(P)}$ and *Placebo Swing Industry*$_{j,T(P)}$, constructed using *Placebo Swing State*$_{s,T(P)}$. Figure 3 shows the distribution of the 1,000 estimated β_1 coefficients with their 99% confidence intervals. Notice that randomizing the identity of swing states produces a wide range of coefficients (between -1.85 and 2.30, with an average of -0.08). The red cross corresponds to the coefficient of $IV_{i,T(P)}$ in our baseline regression (which is equal to 1.663 and significant at the 1% level).

5 Effects of Politically Motivated Trade Protection

In this section, we use our instrument for TTBs 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. To shed light on the mechanisms behind these distributional effects, we then show that trade protection decreases imports and increases prices in protected industries, increasing production costs in downstream industries.

5.1 Employment Effects

The results reported in Section 4.2 show that our instrument predicts the level of protection granted to an industry during executive first terms, when the president can be re-elected. In what follows, we use our instrument to examine the effects of politically motivated trade protection on employment growth during an executive's first term and during the entire presidency. Our analysis is thus focused on the two-term presidencies of Bill Clinton, George W. Bush, and Barack Obama.

We first consider the direct and indirect effects of trade protection on manufacturing industries, by estimating the following regression by 2SLS:

$$\begin{aligned} \Delta L_{j,T(P)} \;&=\; \beta_0 + \beta_1 \mathit{Direct\ Tariff\ Exposure}_{j,T(P)} + \beta_2 \mathit{Downstream\ Tariff\ Exposure}_{j,T(P)} \\ &\quad + \beta_3 \mathit{Upstream\ Tariff\ Exposure}_{j,T(P)} + \beta_4 Z_{j,T(P)} + \delta_j + \delta_P + \varepsilon_{j,P}, \end{aligned} \tag{7}$$

where $\Delta L_{j,T(P)}$ is the growth rate of employment in SIC4 industry j during the first term of presidency P. When studying the effects at the presidential level, we define the dependent variable over two terms.[34] In all specifications, we include SIC4 sector fixed effects (δ_j). 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). We also include presidency fixed effects (δ_P) to account for broad macroeconomic and political factors. We cluster standard errors at the SIC3 level.

The tariff exposure variables defined in equations (1)-(3) are measured during the first term T of president P, instrumented by the corresponding IVs:[35] direct exposure is instru-

[34] For presidency P ending in year t, $\Delta L_{j,P} = \ln(\mathit{Employment}_{j,t}) - \ln(\mathit{Employment}_{j,t-8})$.

[35] These variables are expressed in levels. Recall, however, that their variation reflects policy decisions (e.g., the imposition of duties and the revocation or renewal of existing duties).

mented by $IV_{j,T(P)}$, downstream exposure by $Downstream\ IV_{j,T(P)} \equiv \sum_{i=1}^{N} \omega_{i,j} IV_{i,T(P)}$, and the upstream exposure by $Upstream\ IV_{j,T(P)} \equiv \sum_{i=1}^{N} \theta_{j,i} IV_{i,T(P)}$. 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 matrix $Z_{j,T(P)}$ of the corresponding swing industry variables not interacted with petitioning experience.[36]

TTBs 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 protection on the entire US economy, we include all industries in our sample and estimate:

$$\begin{aligned} \Delta L_{j,T(P)} &= \beta_0 + \beta_1 Downstream\ Tariff\ Exposure_{j,T(P)} + \beta_2 Upstream\ Tariff\ Exposure_{j,T(P)} \\ &\quad + \beta_3 Z_{j,T(P)} + \delta_j + \delta_P + \varepsilon_{j,P}. \end{aligned} \tag{8}$$

Notice that the variable $Direct\ Tariff\ Exposure_{j,T(P)}$ cannot be included in this regression, since it cannot be defined for all 479 SIC4 sectors of the economy.[37]

Equations (7) and (8) allow for the effects of politically motivated protection during executive first terms to take time to manifest themselves. We also estimate the corresponding term-level regressions, which identify the employment effects of politically motivated protection during executive first terms only.

Main Findings

Table 4 reports our baseline 2SLS results. 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. Notice that the KP F-statistics are always above the critical value of 7 (with multiple endogenous variables) based on a 10% maximal IV size, indicating that our instruments are strong. The reduced-form regressions can be found in Table A-6; the coefficients of the instruments have the same signs as in Table 4. The corresponding instruments are always positive and significant at the 1% level in the first stage, as shown in Table A-7.

[36] These are $Swing\ Industry_{j,T(P)}$, $Downstream\ Swing\ Industry_{j,T(P)} \equiv \sum_{i=1}^{N} \omega_{i,j} Swing\ Industry_{i,T(P)}$, and $Upstream\ Swing\ Industry_{j,T(P)} \equiv \sum_{i=1}^{N} \theta_{j,i} Swing\ Industry_{i,T(P)}$.

[37] $Direct\ Tariff\ Exposure_{j,T(P)}$ cannot be defined for sectors in which there cannot be tariffs by definition (non-tradable sectors such as construction or healthcare services). One could assign $Direct\ Tariff\ Exposure_{j,T(P)} = 0$ for these industries. However, the recent literature on shift-share instruments recommend excluding industries with "missing" shocks since they cannot be identified (Borusyak *et al.*, 2022).

Column 1 reports the results of estimating (7) at the term level. The coefficient of *Direct Tariff Exposure*$_{j,T(P)}$ is positive and significant, indicating that TTBs foster employment growth in protected industries. In terms of magnitude, the estimates in column 1 imply that a one percentage point increase in predicted *Direct Tariff Exposure*$_{j,T(P)}$ increases the growth rate of employment in protected industries by 0.6 percentage points. Looking at the effects along supply chains, the coefficient of *Downstream Tariff Exposure*$_{j,T(P)}$ is negative though not statistically significant.

Table 4

The Effects of Trade Protection on Employment Along Supply Chains

	Term		Presidency	
	Manufacturing Industries	All Industries	Manufacturing Industries	All Industries
	(1)	(2)	(3)	(4)
Direct Tariff Exposure$_{j,T(P)}$	0.557***		0.596***	
	(0.184)		(0.191)	
Downstream Tariff Exposure$_{j,T(P)}$	-0.696	-0.740**	-1.301**	-1.114**
	(0.457)	(0.311)	(0.516)	(0.514)
Upstream Tariff Exposure$_{j,T(P)}$	0.073	0.165	0.114	0.445
	(0.392)	(0.298)	(0.344)	(0.304)
Sector FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	No	No
Presidency FE	No	No	Yes	Yes
Observations	1,175	1,436	1,175	1,436
KP F-statistic	36.5	72.5	36.5	72.5

The table reports 2SLS estimates. In columns 1 and 2 (3 and 4), the dependent variable is $\Delta L_{j,T(P)}$ ($\Delta L_{j,P}$), the log change of employment in SIC4 industry j during the first term T of presidency P (presidency P). The tariff variables capture exposure to trade protection, as measured by (1)-(3), instrumented using the corresponding IV variables. The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). The sample covers the period 1993-2016. In columns 1 and 3 (2 and 4), it includes all manufacturing sectors (all sectors). Observations are weighted by 1988 employment. Sector fixed effects are defined at the SIC4 level. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Column 2 reports the results of estimating (8) at the term level. This specification allows us to identify the effects of politically motivated protection on the entire US economy, including non-manufacturing sectors that are indirectly exposed to trade protection. The coefficient of *Downstream Tariff Exposure*$_{j,T(P)}$ indicates that a one percentage point increase in predicted input protection decreases downstream employment growth by 0.74 percentage points.

The remaining specifications consider employment effects over entire presidencies. The coefficient of *Direct Tariff Exposure*$_{j,T(P)}$ in column 3 implies that the positive employment on protected industries persist throughout the presidency. Notice that the coefficients of *Downstream Tariff Exposure*$_{j,T(P)}$ in the same column is now significant and larger in magnitude than the corresponding estimate in column 1, suggesting that the negative effects of trade protection on downstream industries take time to manifest. Based on the estimates in column 3, a one percentage point increase in predicted *Downstream Tariff Exposure*$_{j,P}$ decreases employment growth by 1.3 percentage points. When looking at the entire economy, the estimates in column 4 imply that a one percentage point increase in predicted *Downstream Tariff Exposure*$_{j,P}$ decreases employment growth in all downstream sectors by 1.1 percentage points.

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 they are assigned to it (Imbens and Angrist, 1994). Our analysis thus captures the effects of politically driven protectionist measures identified by our instrument. It is also noteworthy to compare the 2SLS estimates of Table 4 with the corresponding OLS estimates in Table A-5. As discussed at the start of Section 4, we expect the OLS estimates to be downward biased (in absolute value) due to potential omitted variables. In line with this argument, the coefficients for *Direct Tariff Exposure*$_{j,T(P)}$ in Table A-5 are close to zero and not statistically significant; the coefficients of *Downstream Tariff Exposure*$_{j,T(P)}$ have the correct sign, but are much smaller in magnitude compared to Table 4 and are not always significant.

We next compute the number of counterfactual jobs gained and lost due to politically motivated trade protection, following the methodology of Acemoglu *et al.* (2016). Our approach estimates what employment would have been in the absence of TTBs against China that were driven by swing-state politics.

For each industry j during presidency P, we calculate the employment effects of politically motivated TTBs introduced in the first term. Trade protection generates job gains in protected industries, but job losses in downstream industries (those using protected products as inputs). Aggregating across all industries and the three two-term presidencies (Clinton, Bush, and Obama) covering 1993-2016, counterfactual employment changes are given by:

$$\Delta L = \underbrace{\sum_{j,P} L_{j,P}\left(1 - e^{-\hat{\beta}_1 \times \textit{Direct Tariff Exposure}_{j,T(P)} \times \tilde{R}^2}\right)}_{\text{Job Gains in Protected Industries}} + \underbrace{\sum_{j,P} L_{j,P}\left(1 - e^{-\hat{\beta}_2 \times \textit{Downstream Tariff Exposure}_{j,T(P)} \times \tilde{R}^2}\right)}_{\text{Job Losses in Downstream Industries}},$$

where $L_{j,P}$ is the actual employment level in industry j at the end of presidency P. The coefficients $\hat{\beta}_1 > 0$ and $\hat{\beta}_2 < 0$ are the 2SLS estimates from Table 4, which show that TTBs increase employment in directly protected industries but decrease it in downstream industries. The partial-R^2 (0.049) of the first-stage for $\textit{Direct Tariff Exposure}_{j,T(P)}$ scales the tariff exposure to isolate the portion of trade protection that our instrument attributes to swing-state politics, ensuring that we capture only politically motivated protection.[38]

When focusing on manufacturing sectors, the estimates in column 3 of Table 4 imply around 257,000 jobs gained and 434,000 jobs lost, resulting in net US job losses of around 177,000 during 1993-2016, or almost 7,500 net job losses per year. When considering the entire economy, the estimates in column 4 imply around 46,000 net job losses per year.[39]

We can also compute counterfactual job gains and losses at the state level by replacing $L_{j,P}$ with $L_{j,s,P}$ (employment in industry j in state s at the end of presidency P).[40] The results indicate that all states experience net job losses from politically motivated trade protection. However, there is a small positive correlation (0.16, significant at the 5% level) between the ratio of job gains to job losses and $\textit{Swing State}_{s,T(P)}$, indicating that states with a higher probability of being pivotal fare relatively better. Overall, our results imply that TTBs motivated by swing-state politics foster employment growth in the protected industries, but give rise to net employment losses in the United States at large and in individual states.

Robustness Checks

Here, we discuss a series of additional estimations to verify the robustness of our main findings. The first and most important of these robustness checks is related to the identification strategy: one may be concerned about the endogeneity of the shares in our shift-share instru-

[38] When our instrument is valid and there is no measurement error, this partial-R^2 adjustment provides a consistent estimate of the contribution of swing-state politics to trade protection. Following Acemoglu *et al.* (2016), the counterfactual assumes that all other factors affecting employment would remain unchanged in the absence of politically motivated TTBs against China.

[39] While our estimates focus on politically motivated TTBs over more than two decades, their order of magnitude is broadly comparable to the short-run effects of the 2018–2019 trade war. Flaaen and Pierce (2024) estimate that tariffs introduced during that episode led to approximately 320,000 manufacturing job losses, of which around 230,000 were attributable to higher input costs.

[40] The caveat in this exercise is that we use the $\hat{\beta}$ estimates from equation (7), which are at the industry rather than state level (since trade protection is industry-specific and applied nationally).

ment. For example, an industry's historical petitioning experience may be correlated with other potential drivers of employment growth. Even if the political shocks are "as-good-as" randomly assigned, non-random exposure to the shocks would give rise to an omitted variable bias in our 2SLS estimates.

To address this concern, we apply the "recentering" methodology proposed by Borusyak and Hull (2023), subtracting from our IV variables the "expected instruments" created by randomizing the identity of swing states. We consider the same randomization exercise carried out in the placebo exercise in Section 4.3. We perform 1,000 randomizations of swing states, consisting of independent random draws of swing states for each presidential term. From each randomization, we obtain a variable $\textit{Placebo Swing State}_{s,T(P)}$, which we use to construct $\textit{Placebo IV}_{s,T(P)}$. By averaging across the 1,000 draws, we obtain $\textit{Expected IV}_{j,T(P)}$.

Table 5

The Effects of Trade Protection on Employment Along Supply Chains (Recentered Instruments)

	Term		Presidency	
	Manufacturing Industries	All Industries	Manufacturing Industries	All Industries
	(1)	(2)	(3)	(4)
$\textit{Direct Tariff Exposure}_{j,T(P)}$	0.547***		0.579***	
	(0.179)		(0.181)	
$\textit{Downstream Tariff Exposure}_{j,T(P)}$	-0.691	-0.744**	-1.279**	-1.104**
	(0.457)	(0.310)	(0.510)	(0.505)
$\textit{Upstream Tariff Exposure}_{j,T(P)}$	0.075	0.181	0.127	0.460
	(0.381)	(0.294)	(0.334)	(0.301)
Sector FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	No	No
Presidency FE	No	No	Yes	Yes
Observations	1,175	1,436	1,175	1,436
KP F-statistic	30.1	67.7	30.1	67.7

The table reports 2SLS estimates. In columns 1 and 2 (3 and 4), the dependent variable is $\Delta L_{j,T(P)}$ ($\Delta L_{j,P}$), the log change of employment in SIC4 industry j during the first term T of presidency P (presidency P). The tariff variables capture exposure to trade protection, as measured by (1)-(3), instrumented using the corresponding IV variables. The instruments are recentered using $\textit{Expected IV}_{j,T(P)}$ and the corresponding downstream and upstream variables. The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). The sample covers the period 1993-2016. In columns 1 and 3 (2 and 4), it includes all manufacturing sectors (all sectors). 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 5 reports the results in which we use $\textit{Expected IV}_{j,T(P)}$ (and the corresponding downstream and upstream variables) to recenter the instruments. These results suggest that our 2SLS estimates on the employment effects of trade protection are robust to addressing concerns about potential omitted variable bias due to non-random exposure: the sign and the magnitude of the coefficients are unaffected when we generate counterfactual political shocks to recenter our instruments.

In the Appendix, we report the results of a series of additional robustness checks. In our main analysis, we simply code whether an industry is protected by any TTB (AD duties, CV duties, or safeguards). The results continue to hold if we use information on the share of products within a sector that are subject to these measures (Table A-8) or if we consider only AD duties, the most commonly used TTB (Table A-9). In Table A-10, we further control for MFN tariffs applied by the United States for industry j ($\textit{Direct MFN}_{j,T(P)}$), as well as the corresponding tariffs applied to j's input industries ($\textit{Downstream MFN}_{j,T(P)}$) and output industries ($\textit{Upstream MFN}_{j,T(P)}$). Again, coefficients of the variables $\textit{Direct Tariff Exposure}_{j,T(P)}$ and $\textit{Downstream Tariff Exposure}_{j,T(P)}$ are unaffected. The coefficients of the MFN tariff variables are not significant. This is not surprising, given that MFN tariffs are bound to the levels agreed upon during multilateral negotiations and thus exhibit little within-industry variation. The results continue to hold if we cluster standard errors at a broader industry level (SIC2) (Table A-11) or if we exclude the diagonal of the input-output matrix in the construction of the indirect tariff exposure variables (Table A-12).

5.2 Mechanisms: Effects on Imports and Prices

The results reported in Table 4 show that politically motivated protection fosters employment growth in protected sectors, but decreases growth in downstream sectors. In this section, we explore the mechanisms behind these effects, examining the impact of politically motivated trade protection on imports and prices.

We first examine the effects of politically motivated protection on imports from China, the country targeted by the TTBs. We use data from the UN Comtrade database to construct the variable $\Delta \textit{Import Values}_{j,T(P)}$ ($\Delta \textit{Import Quantities}_{j,T(P)}$), the log change of US import values (quantities) from China in SIC4 industry j during either the first term or the entire presidency P.[41]

[41] To make the value and quantity specifications comparable, we restrict the sample to HS6 codes that report quantities in the same unit (i.e., kilograms) for our sample period, and convert the data to the SIC4 level using the HS1992-SIC4 concordance.

The negative and significant coefficients of *Direct Tariff Exposure*$_{j,T(P)}$ in Table 6 indicate that politically motivated TTBs introduced during the first term of a presidency reduce both import values and import quantities in targeted industries, during first terms and during the entire presidency.[42] Table A-13 in the Appendix shows that politically motivated TTBs against China had no significant effect on import values or quantities from other countries. This suggests that politically motivated TTBs on China did not result in trade diversion on average.

Table 6

The Effects of Trade Protection on Imports

	Term		Presidency	
Dependent variable:	Import Values	Import Quantities	Import Values	Import Quantities
	(1)	(2)	(3)	(4)
Direct Tariff Exposure$_{j,T(P)}$	-6.456***	-8.778***	-6.375***	-7.533***
	(1.316)	(1.799)	(1.674)	(1.681)
Sector FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	No	No
Presidency FE	No	No	Yes	Yes
Observations	600	600	600	600
KP F-statistic	29.6	29.6	29.6	29.6

The table reports 2SLS estimates. In column 1 (2), the dependent variable is Δ*Imports Values*$_{j,T(P)}$ (Δ*Import Quantities*$_{j,T(P)}$), the log change of US import values (quantities) from China in SIC4 industry j during the first term of presidency P. In column 3 (4), the dependent variable is Δ*Imports Values*$_{j,P}$ (Δ*Import Quantities*$_{j,P}$), the log change of US import values (quantities) from China in SIC4 industry j during presidency P. *Direct Tariff Exposure*$_{j,T(P)}$ is instrumented using $IV_{j,T(P)}$. The regressions also include *Swing Industry*$_{j,T(P)}$ (coefficients not reported). The sample covers the period 1993-2016 and includes manufacturing sectors. 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 7 considers the effects on domestic prices. The goal of this table is to explore the mechanisms behind the positive (negative) employment effects of politically motivated protection on employment in protected (downstream) industries documented in Table 4 and its robustness checks.[43] To this purpose, we use data on producer price indices (PPI) from

[42] If we replace import values with unit values, the coefficient of *Direct Tariff Exposure*$_{j,T(P)}$ is positive and statistically significant at the 5% level in first terms, and positive but not significant for the the entire presidency. In line with several studies on the effects of the 2018 Trump's tariffs (e.g., Amiti *et al.*, 2019; Cavallo *et al.*, 2021), these results indicate the foreign exporters did not reduce their (pre-tariff) prices, implying that the effects of trade protection have been passed on entirely to US importers.

[43] We do not consider the effects on industries that supply the protected ones, since the coefficient of *Upstream Tariff Exposure*$_{j,T(P)}$ is not statistically significant in Table 4 and its robustness checks.

the US Bureau of Labor Statistics (BLS), and construct $\Delta Producer\ Price_{j,T(P)}$, the growth rate of prices in SIC4 industry j during presidency P.[44] Combining PPI data with input-output data from the BEA, we also construct the variable $\Delta Input\ Price_{j,T(P)}$, the growth rate of input prices faced by downstream industry j.

The results reported in Table 7 show that politically motivated TTBs increase prices in protected (manufacturing) industries, as well as production costs in downstream (manufacturing and non-manufacturing) industries.

Table 7

The Effects of Trade Protection on Producer and Input Prices

	Term		Presidency	
	Producer Price	Input Price	Producer Price	Input Price
	(1)	(2)	(3)	(4)
Direct Tariff Exposure$_{j,T(P)}$	0.137***		0.276***	
	(0.028)		(0.045)	
Downstream Tariff Exposure$_{j,T(P)}$		0.092**		0.449***
		(0.046)		(0.066)
Sector FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	No	No
Presidency FE	No	No	Yes	Yes
Observations	658	1,437	658	1,437
KP F-statistic	114.1	181.4	114.1	181.4

The table reports 2SLS estimates. In column 1 (3), the dependent variable is $\Delta Producer\ Price_{j,P}$, the growth rate producer prices in downstream industry j during the first term of presidency P (presidency P). In column 2 (4), the dependent variable is $\Delta Input\ Price_{j,P}$, the growth rate of input prices faced by producers in downstream industry j during the first term of presidency P (presidency P).. *Direct Tariff Exposure*$_{j,T(P)}$ (*Downstream Tariff Exposure*$_{j,T(P)}$) is instrumented using $IV_{j,T(P)}$ (*Downstream* $IV_{j,T(P)}$). The sample covers the period 1993-2016. In columns 1 and 3 (2 and 4), it includes all manufacturing sectors (all sectors). Columns 1-3 (2-4) include *Swing Industry*$_{j,T(P)}$ (*Downstream Swing Industry*$_{j,T(P)}$) (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.

6 Conclusion

The US-China trade war triggered by the special tariffs introduced during President Trump's first term stimulated a flourishing literature on the costs of trade protection. In this paper, we show that, well before President Trump took office, the United States had been using protectionist measures against China, in the form of AD duties and other TTBs. Combining

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

detailed information on these measures with US input-output data, we examine the effects of protection along supply chains.

To address concerns about the endogeneity of trade policy, we propose a new shift-share instrument for US TTBs. Identification relies on changes in the identity of swing states across electoral terms, which generate plausibly exogenous political shocks. Exposure to these shocks varies across industries, depending on their geographic distribution across states, their historical experience in the complex process of petitioning for TTBs, and input-output linkages between them. We show that the instrument is a strong predictor of the level of trade protection granted to an industry during executive first terms, when the incumbent president can be re-elected.

We use our instrument to identify the effects of politically motivated trade protection on directly and indirectly exposed industries. We find that TTBs driven by swing-state politics generate winners and losers across industries: they foster employment growth in protected industries, but hinder growth in downstream industries. The effects are sizeable and continue to hold when we address concerns about non-random industry exposure to the political shocks and in a battery of additional robustness checks. When considering manufacturing industries, our baseline two-stage least squares (2SLS) estimates imply net job losses of around 177,000 (or 7,500 per year) caused by politically motivated trade protection during 1993-2016, covering the two-term presidencies of Bill Clinton, George W. Bush, and Barack Obama. These results resonate with those of Flaaen and Pierce (2024), who find that the special tariffs introduced under President Trump in 2018-2019 led to net job losses in manufacturing. When extending the analysis to all sectors in the economy, the net job losses increase to 1.1 million, corresponding to around 46,000 net job losses per year.

Our analysis has important implications regarding the ongoing policy debate about the use of protectionist measures against China in the United States and other countries. Recent years have seen an unprecedented backlash against international trade and globalization. Politicians in high-income countries have been pointing at increasing import competition from China as the cause for the decline in manufacturing jobs and have extensively used protectionist measures against China. Our analysis shows that, rather than fostering employment growth, these protectionist measures give rise to additional job losses.

Our findings also provide new arguments in the debate about the Electoral College. 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.[45] As a result, in several elections, the outcome has gone against the popular vote, including in 2000 (when Al Gore won the popular vote but George W. Bush won in the Electoral College) and 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. Our paper shows that swing-state politics affects trade policy choices, giving rise to distributional effects: to get re-elected, incumbent executives implement protectionist measures that are beneficial to industries that are important in swing states, but are detrimental to downstream industries.

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

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Appendices

A-1 Product to Industry Concordance

As explained in Section 3, the Temporary Trade Barriers Database (TTBD) contains detailed information on AD duties and other protectionist measures (CV duties and safeguards). For each case, it provides information on the products under investigation 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:[46]

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.[47] 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. 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 case from the ITC case descriptions.

[46] 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.

[47] 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 cases before 1988, we match each TSUSA code with a corresponding HS code using the correspondence table provided by Feenstra (1996).

A-2 Identity of Swing States

Our identification strategy relies on changes in the identity of swing states across presidential elections, which are assumed to be driven by exogenous political shocks. In what follows we verify that the variable $\textit{Swing State}_{s,T(P)}$ is uncorrelated with various state-level characteristics. The results are reported in Table A-1.

We first consider state-level exposure to import competition. Previous studies show that exposure to import competition from China can affect electoral outcomes (Autor *et al.*, 2020; Che *et al.*, 2022). One may thus be concerned that whether or not a state is classified as swing in a presidential election may be correlated with the extent to which its industries have been exposed to such competition. To verify whether this is the case, we construct the variable:

$$\textit{Import Competition}_{s,T(P)} = \sum_{j} \phi_{j,s} \frac{\textit{Imports}_{j,T(P)}}{\textit{Production}_{j,1988} + \textit{Imports}_{j,1988}}, \tag{9}$$

where $\phi_{j,s}$ is the 1988 share of employment in manufacturing industry j in state s over total manufacturing employment in that state. Data on imports from China and US production come from United Nations (UN) Comtrade and NBER-CES Manufacturing Industry Database, respectively.[48] The results reported in columns 1-2 of Table A-1 show that the extent to which a state s has been exposed to import competition (in levels or changes) during a term T does not affect whether the state is classified as swing in the presidential elections at the end of the term.[49]

We also construct the variables $\textit{Manufacturing Employment}_{s,T(P)}$ and $\textit{Manufacturing Share}_{s,T(P)}$, which respectively measure the log number of workers employed in manufacturing sectors and the share of total employment accounted by manufacturing industries in state s during term T. Columns 5-6 of Table A-1 show that the identity of swing states at the end of a term is not significantly correlated with these variables (expressed in levels or changes).

The results of Table 1 show that our instrument is a strong predictor of the level of protection granted to an industry during executive first terms, when the president has re-election motives. The causal interpretation of these findings requires that trade protection does not affect the identity of swing states. To rule out this potential reverse causality, we

[48]The results are unaffected if $\textit{Import Competition}_{s,T(P)}$ is based on US imports from all countries.

[49]Column 2 excludes the first term of President Bush Sr. since import data is available from 1991 only.

construct the variable:

$$Trade\ Protection_{s,T(P)} = \sum_j \phi_{j,s}\, Trade\ Protection_{j,T(P)}, \tag{10}$$

where $\phi_{j,s}$ is the 1988 share of employment in manufacturing industry j in state s over total manufacturing employment in that state and *Trade Protection*$_{j,T(P)}$ is an indicator variable equal to 1 if SIC4 j is covered by TTBs during term T. Columns 7 and 8 of Table A-1 shows that whether a state is classified as swing at the end of a term is uncorrelated with the extent to which its industries have been protected during that term (in level or changes).

Table A-1

The Identity of Swing States and State-Level Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Import Competition$_{s,T(P)}$	-0.064							
	(0.074)							
Δ*Import Competition*$_{s,T(P)}$		-0.027						
		(0.016)						
Manufacturing Employment$_{s,T(P)}$			0.008					
			(0.007)					
Δ*Manufacturing Employment*$_{s,T(P)}$				0.021				
				(0.017)				
Manufacturing Share$_{s,T(P)}$					0.032			
					(0.069)			
Δ*Manufacturing Share*$_{s,T(P)}$						-0.019		
						(0.141)		
Trade Protection$_{s,T(P)}$							0.019	
							0.032	
Δ*Trade Protection*$_{s,T(P)}$								-0.055
								0.034
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.496	0.503	0.495	0.497	0.494	0.493	0.494	0.503
Observations	400	350	400	400	400	400	400	400

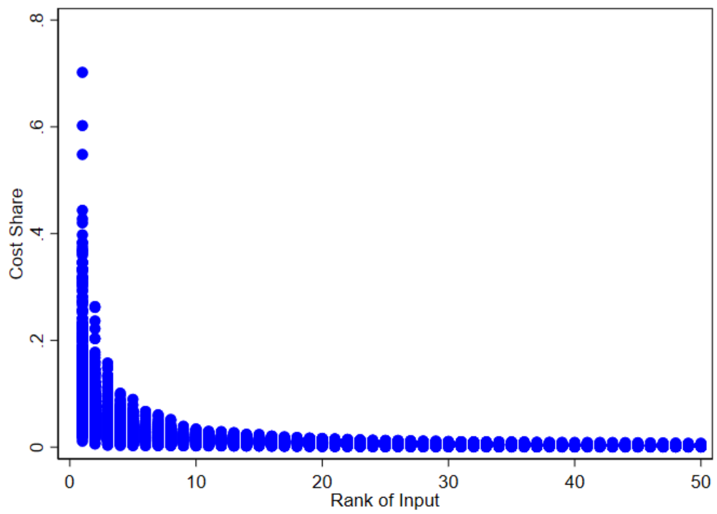
The dependent variable is *Swing State*$_{s,T(P)}$, the probability that state s is a decisive swing state in the presidential elections at the end of term T (of presidency P), based on Strömberg (2008)'s probabilistic voting model. The independent variables (expressed in levels and changes) capture various state characteristics in the four years preceding the elections in year t: the extent to which a state has been exposed to import competition, the log number of workers employed in manufacturing industries in a state, the size of the manufacturing sector (relative to total state-level employment), and the extent to which industries in the state have been previously protected by TTBs. The sample covers the 1989-2020 period. Observations are weighted by 1988 state-level manufacturing employment. Standard errors are clustered at the state level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

A-3 Appendix Figures

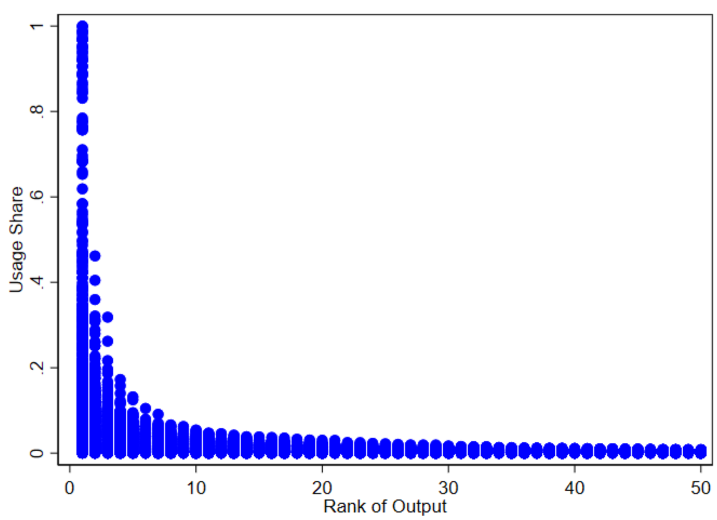
Figure A-1

Distribution of IO Coefficients

(a) Top-50 Input Industries



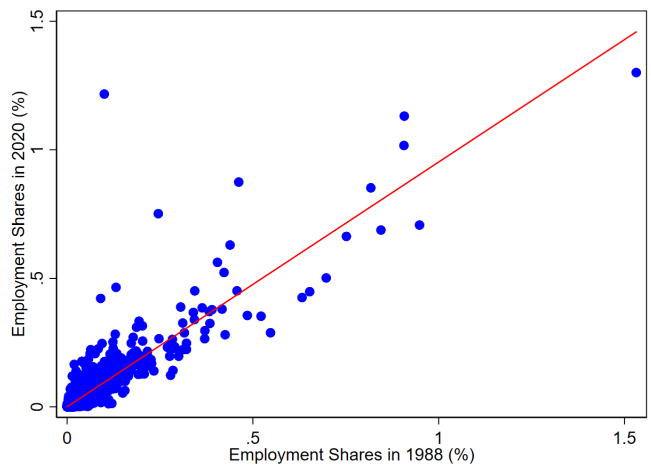
(b) Top-50 Output Industries



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

Figure A-2

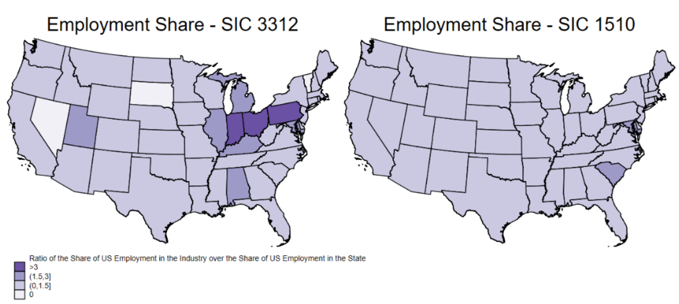
SIC4 Employment Shares by State



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

Figure A-3

Geographical distribution of steel and construction (based on 1988 employment shares)



The maps indicate state-level shares of US employment in industries SIC 3312 ("Blast furnaces and steel mills") and SIC 1510 ("Construction") in 1988 over state-level shares of overall US employment in the same year. The map on the left shows that steel is highly geographically concentrated: three states in the Rust Belt (Indiana, Ohio, and Pennsylvania) account for more than 56% of US employment in steel, though their share of overall US employment is only 13%; the other states have little or no employment in steel. The mean ratio of state-level shares of US employment in steel over state-level shares of total US employment is 0.697. For Indiana, Ohio, and Pennsylvania, this ratio is respectively 6.54, 4.69 and 3.16. The map on the right is for construction, a large non-manufacturing sector that relies heavily on steel as an input (SIC 3312 is the most important input for SIC 1510). This industry is much more geographically dispersed: construction is present in all US states, and state-level employment in construction is generally proportional to the total number of workers in the state: the mean ratio of state-level shares of US employment in construction over state-level shares of total US employment is 0.998. The maximum ratio is 1.69 (for Maryland).

A-4 Appendix Tables

Table A-2

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-3

Descriptive Statistics of Main Variables

Variable	Obs.	Mean	Std. dev.	Min	Max
$\textit{Direct Tariff Exposure}_{j,T(P)}$	3,133	0.143	0.350	0.000	1.000
$\textit{Downstream Tariff Exposure}_{j,T(P)}$	3,829	0.149	0.123	0.002	0.820
$\textit{Upstream Tariff Exposure}_{j,T(P)}$	3,829	0.097	0.169	0.000	1.496
$\textit{Swing Industry}_{j,T(P)}$	3,133	0.003	0.004	0.000	0.042
$IV_{j,T(P)}$	3,133	0.008	0.067	0.000	1.449
$\textit{Experience}_j$	3,133	1.236	3.649	0	64

The table reports descriptive statistics of the main variables used in our analysis, which are defined in Section 3. The variables $\textit{Direct Tariff Exposure}_{j,T(P)}$, $\textit{Swing Industry}_{j,T(P)}$, $\textit{Experience}_j$, and $IV_{j,T(P)}$ are constructed for manufacturing industries. The variables $\textit{Downstream Tariff Exposure}_{j,T(P)}$ and $\textit{Upstream Tariff Exposure}_{j,T(P)}$ are constructed for all industries, using higher-order input-output linkages and including the diagonal of the input-output matrix. The sample covers the period 1989-2020.

Table A-4

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

Sector	Description	Average *Swing Industry*$_{j,T(P)}$	Average *Direct Tariff Exposure*$_{j,T(P)}$
	Swing Industry$_{j,T(P)}$		
3714	Motor vehicle parts and accessories	0.031	0.750
2752	Commercial printing, lithographic	0.031	0.500
3089	Plastics products, n.e.c.	0.031	0.375
2711	Newspapers	0.025	0.000
3711	Motor vehicles and car bodies	0.023	0.000
3312	Blast furnaces and steel mills	0.019	0.750
2599	Furniture and fixtures, n.e.c.	0.019	0.625
3812	Search and navigation equipment	0.018	0.000
3499	Fabricated metal products, n.e.c.	0.017	1.000
3599	Industrial machinery, n.e.c.	0.015	0.375

Sector	Description	*Experience*$_j$	Average *Direct Tariff Exposure*$_{j,T(P)}$
	Experience$_j$		
3312	Blast furnaces and steel mills	64	0.750
2819	Industrial inorganic chemicals, n.e.c.	13	1.000
3714	Motor vehicle parts and accessories	12	0.750
2869	Industrial organic chemicals, n.e.c.	10	1.000
3999	Manufacturing industries, n.e.c.	8	1.000
3494	Valves and pipe fittings, n.e.c.	7	1.000
2821	Plastics materials and resins	7	1.000
3991	Brooms and brushes	7	1.000
3496	Misc. fabricated wire products	7	0.875
2399	Fabricated textile products, n.e.c.	7	0.375

The table lists the top-10 SIC4 sectors with the highest average value of *Swing Industry*$_{j,T(P)}$ during 1989-2020 (top panel) and the highest value of pre-sample *Experience*$_j$ (bottom panel), with the corresponding *Direct Tariff Exposure*$_{j,T(P)}$.

Table A-5

The Effects of Trade Protection on Employment Along Supply Chains
(OLS)

	Term		Presidency	
	Manufacturing Industries	All Industries	Manufacturing Industries	All Industries
	(1)	(2)	(3)	(4)
Direct Tariff Exposure$_{j,T(P)}$	0.014		-0.027	
	(0.029)		(0.040)	
Downstream Tariff Exposure$_{j,T(P)}$	-0.401**	-0.459**	-0.422*	-0.276
	(0.177)	(0.186)	(0.221)	(0.254)
Upstream Tariff Exposure$_{j,T(P)}$	-0.022	-0.094	-0.008	-0.117
	(0.133)	(0.146)	(0.167)	(0.195)
Sector FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	No	No
Presidency FE	No	No	Yes	Yes
Observations	1,175	1,436	1,175	1,436
Adjusted R^2	0.33	0.46	0.48	0.55

The table reports OLS estimates. In columns 1 and 2 (3 and 4), the dependent variable is $\Delta L_{j,T(P)}$ ($\Delta L_{j,P}$), the log change of employment in SIC4 industry j during the first term T of presidency P (presidency P). The tariff variables capture exposure to trade protection, as measured by (1)-(3). The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). The sample covers the period 1993-2016. In columns 1 and 3 (2 and 4), it includes all manufacturing sectors (all sectors). 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

Reduced-Form Results for Table 4

	Term		Presidency	
	Manufacturing Industries	All Industries	Manufacturing Industries	All Industries
	(1)	(2)	(3)	(4)
$IV_{j,T(P)}$	2.269***		2.481***	
	(0.712)		(0.735)	
Downstream $IV_{j,T(P)}$	-1.867*	-3.910**	-4.272***	-5.692**
	(1.090)	(1.836)	(1.510)	(2.877)
Upstream $IV_{j,T(P)}$	-0.642	1.726	0.149	4.255
	(2.519)	(2.611)	(2.073)	(2.737)
Sector FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	No	No
Presidency FE	No	No	Yes	Yes
Observations	1,175	1,436	1,175	1,436
Adjusted R^2	0.40	0.48	0.55	0.57

The table reports the reduced-form results of the 2SLS estimates of Table 4. In columns 1 and 2 (3 and 4), the dependent variable is $\Delta L_{j,T(P)}$ ($\Delta L_{j,P}$), the log change of employment in SIC4 industry j during the first term T of presidency P (pre sidency P). The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). The sample covers the period 1993-2016. In columns 1 and 3 (2 and 4), it includes all manufacturing sectors (all sectors). Observations are weighted by 1988 employment. Sector fixed effects are defined at the SIC4 level. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-7

First-Stage Results for Table 4

Dependent variable:	Direct Tariff Exposure (1)	Downstream Tariff Exposure (2)	Upstream Tariff Exposure (3)
$IV_{j,T(P)}$	4.108***	-0.353***	-0.238
	(0.551)	(0.125)	(0.313)
Downstream $IV_{j,T(P)}$	-7.317**	3.992***	0.297
	(3.090)	(0.241)	(0.585)
Upstream $IV_{j,T(P)}$	-8.029***	-0.716	7.244***
	(2.801)	(0.440)	(0.663)
Direct Tariff $Exposure_{j,T(P)}$		0.067***	0.070***
		(0.018)	(0.024)
Downstream Tariff $Exposure_{j,T(P)}$	2.141***		-0.035
	(0.592)		(0.111)
Upstream Tariff $Exposure_{j,T(P)}$	0.979***	-0.015	
	(0.258)	(0.047)	
Sector FE	Yes	Yes	Yes
Term/Presidency FE	Yes	Yes	Yes
Observations	1,175	1,175	1,175
Adjusted R^2	0.62	0.86	0.77

The table reports the first-stage results of the 2SLS estimates of columns 1 and 3 of Table 4. The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). The sample covers the period 1993-2016 and includes all manufacturing sectors. 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

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

	Term		Presidency	
	Manufacturing Industries	All Industries	Manufacturing Industries	All Industries
	(1)	(2)	(3)	(4)
Direct Tariff Exposure$_{j,T(P)}$	3.168**		3.237**	
	(1.427)		(1.322)	
Downstream Tariff Exposure$_{j,T(P)}$	-4.110*	-2.897**	-6.194**	-4.269**
	(2.396)	(1.264)	(2.406)	(2.045)
Upstream Tariff Exposure$_{j,T(P)}$	-2.175	0.968	-1.682	2.570
	(2.996)	(1.699)	(2.483)	(1.688)
Sector FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	No	No
Presidency FE	No	No	Yes	Yes
Observations	1,175	1,436	1,175	1,436
KP F-statistic	13.3	38.6	13.3	38.6

The table reports 2SLS estimates. In columns 1 and 2 (3 and 4), the dependent variable is $\Delta L_{j,T(P)}$ ($\Delta L_{j,P}$), the log change of employment in SIC4 industry j the first term T of presidency P (during presidency P). The tariff variables capture direct and indirect exposure to trade protection (measured as the share of HS6 products within industry j subject to TTBs), instrumented using the corresponding IV variables. The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). The sample covers the period 1993-2016. In columns 1 and 3 (2 and 4), it includes all manufacturing sectors (all sectors). 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

The Effects of Trade Protection on Employment Along Supply Chains
(AD Duties Only)

	Term		Presidency	
	Manufacturing Industries	All Industries	Manufacturing Industries	All Industries
	(1)	(2)	(3)	(4)
Direct Tariff Exposure$_{j,T(P)}$	0.552***		0.593***	
	(0.180)		(0.188)	
Downstream Tariff Exposure$_{j,T(P)}$	-0.539	-0.750**	-1.139**	-1.130**
	(0.390)	(0.316)	(0.480)	(0.519)
Upstream Tariff Exposure$_{j,T(P)}$	0.037	0.185	0.086	0.486
	(0.412)	(0.318)	(0.365)	(0.327)
Sector FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	No	No
Presidency FE	No	No	Yes	Yes
Observations	1,175	1,436	1,175	1,436
KP F-statistic	36.7	72.1	36.7	72.1

The table reports 2SLS estimates. In columns 1 and 2 (3 and 4), the dependent variable is $\Delta L_{j,T(P)}$ ($\Delta L_{j,P}$), the log change of employment in SIC4 industry j during the first term T of presidency P (presidency P). The tariff variables capture direct and indirect exposure to trade protection (AD only), instrumented using the corresponding IV variables. The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). The sample covers the period 1993-2016. In columns 1 and 3 (2 and 4), it includes all manufacturing sectors (all sectors). Observations are weighted by 1988 employment. Sector fixed effects are defined at the SIC4 level. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-10

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

	Term		Presidency	
	Manufacturing Industries	All Industries	Manufacturing Industries	All Industries
	(1)	(2)	(3)	(4)
Direct Tariff Exposure$_{j,T(P)}$	0.571***		0.611***	
	(0.186)		(0.193)	
Downstream Tariff Exposure$_{j,T(P)}$	-0.662	-0.740**	-1.286**	-1.120**
	(0.478)	(0.312)	(0.535)	(0.513)
Upstream Tariff Exposure$_{j,T(P)}$	-0.031	0.160	-0.023	0.420
	(0.407)	(0.302)	(0.358)	(0.314)
Direct MFN$_{j,T(P)}$	0.006		0.007	
	(0.005)		(0.006)	
Downstream MFN$_{j,T(P)}$	0.002	-0.000	-0.006	-0.004
	(0.011)	(0.008)	(0.017)	(0.013)
Upstream MFN$_{j,T(P)}$	-0.033	-0.002	-0.040	-0.009
	(0.034)	(0.012)	(0.035)	(0.020)
Sector FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	No	No
Presidency FE	No	No	Yes	Yes
Observations	1,175	1,436	1,175	1,436
KP F-statistic	30.3	62.5	30.3	62.5

The table reports 2SLS estimates. The table reports 2SLS estimates. In columns 1 and 2 (3 and 4), the dependent variable is $\Delta L_{j,T(P)}$ ($\Delta L_{j,P}$), the log change of employment in SIC4 industry j during the first term T of presidency P (presidency P). The tariff variables capture direct and indirect exposure to trade protection, instrumented using the corresponding IV variables. The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). The sample covers the period 1993-2016. In columns 1 and 3 (2 and 4), it includes all manufacturing sectors (all sectors). 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

The Effects of Trade Protection on Employment Along Supply Chains
(Broader Industry Clusters)

	Term		Presidency	
	Manufacturing Industries	All Industries	Manufacturing Industries	All Industries
	(1)	(2)	(3)	(4)
Direct Tariff Exposure$_{j,T(P)}$	0.557**		0.596**	
	(0.208)		(0.213)	
Downstream Tariff Exposure$_{j,T(P)}$	-0.696*	-0.740*	-1.301***	-1.114
	(0.362)	(0.384)	(0.426)	(0.709)
Upstream Tariff Exposure$_{j,T(P)}$	0.073	0.165	0.114	0.445
	(0.344)	(0.304)	(0.345)	(0.347)
Sector FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	No	No
Presidency FE	No	No	Yes	Yes
Observations	1,175	1,436	1,175	1,436
KP F-statistic	23.1	57.3	23.1	57.3

The table reports 2SLS estimates. The table reports 2SLS estimates. In columns 1 and 2 (3 and 4), the dependent variable is $\Delta L_{j,T(P)}$ ($\Delta L_{j,P}$), the log change of employment in SIC4 industry j during the first term T of presidency P (presidency P). The tariff variables capture direct and indirect exposure to trade protection, instrumented using the corresponding IV variables. The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). The sample covers the period 1993-2016. In columns 1 and 3 (2 and 4), it includes all manufacturing sectors (all sectors). Observations are weighted by 1988 employment. Sector fixed effects are defined at the SIC4 level. Standard errors are clustered at the SIC2 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-12

The Effects of Trade Protection on Employment Along Supply Chains
(Excluding the Diagonal of the Input-Output Matrix)

	Term		Presidency	
	Manufacturing Industries	All Industries	Manufacturing Industries	All Industries
	(1)	(2)	(3)	(4)
Direct Tariff Exposure$_{j,T(P)}$	0.510**		0.555**	
	(0.221)		(0.245)	
Downstream Tariff Exposure$_{j,T(P)}$	-0.546	-0.832**	-1.161**	-1.241**
	(0.417)	(0.348)	(0.506)	(0.539)
Upstream Tariff Exposure$_{j,T(P)}$	0.250	-0.065	0.303	0.262
	(0.535)	(0.285)	(0.502)	(0.316)
Sector FE	Yes	Yes	Yes	Yes
Presidency FE	Yes	Yes	No	No
Term FE	No	No	Yes	Yes
Observations	1,175	1,436	1,175	1,436
KP F-statistic	23.1	60.3	23.1	60.3

The table reports 2SLS estimates. In columns 1 and 2 (3 and 4), the dependent variable is $\Delta L_{j,T(P)}$ ($\Delta L_{j,P}$), the log change of employment in SIC4 industry j during the first term T of presidency P (presidency P). The tariff variables capture direct and indirect exposure to trade protection (excluding the diagonal of the input-output matrix), instrumented using the corresponding IV variables. The regressions include the corresponding direct, downstream and upstream *Swing Industry* variables (coefficients not reported). The sample covers the period 1993-2016. In columns 1 and 3 (2 and 4), it includes all manufacturing sectors (all sectors). 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 of Trade Protection on Imports

(Non-China)

	Term		Presidency	
Dependent variable:	Import Values	Import Quantities	Import Values	Import Quantities
	(1)	(2)	(3)	(4)
Direct Tariff Exposure$_{j,T(P)}$	-0.045	-0.263	0.060	-0.058
	(0.109)	(0.427)	(0.218)	(0.402)
Sector FE	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	No	No
Presidency FE	No	No	Yes	Yes
Observations	600	600	600	600
KP F-statistic	29.6	29.6	29.6	29.6

The table reports 2SLS estimates. In column 1 (2), the dependent variable is Δ*Imports Values* $RoW_{j,T(P)}$ (Δ*Import Quantities* $RoW_{j,T(P)}$), the log change of US import values (quantities) from the rest of the world (i.e., non-China) in SIC4 industry j during the first term of presidency P. In column 3 (4), the dependent variable is Δ*Imports Values*$_{j,P}$ (Δ*Import Quantities*$_{j,P}$), the log change of US import values (quantities) from the rest of the world in SIC4 industry j during presidency P. *Direct Tariff Exposure*$_{j,T(P)}$ is instrumented using $IV_{j,T(P)}$. The regressions also include *Swing Industry*$_{j,T(P)}$ (coefficients not reported). The sample covers the period 1993-2016 and includes manufacturing sectors. 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.