Trade Protection Along Supply Chains*

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Abstract

During the last decades, the United States has applied increasingly high trade protection against China. We combine detailed information on US antidumping (AD) duties — the most widely used trade barrier — with US input-output data to study the effects of trade protection against China along supply chains. To deal with endogeneity concerns, we propose a new instrument for AD duties, which combines exogenous variation in the political importance of industries across electoral terms with their historical experience in AD proceedings. We estimate the effects of protection on directly exposed and indirectly exposed (downstream and upstream) industries. We find that AD duties have a net negative impact on US jobs: they reduce employment growth in downstream industries, with no significant effects in protected and upstream industries. We provide evidence for the mechanisms behind the negative effects of protection along supply chains: AD duties decrease imports and raise prices in protected industries, increasing production costs in downstream industries.

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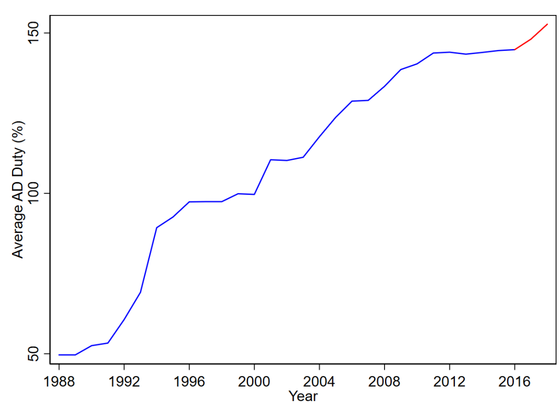
1 Introduction

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 protectionist measures that have been imposed to curb this rise in Chinese import competition. Recent studies have examined the effects of the special measures introduced in 2018 by the Trump administration and the resulting retaliation (e.g. Amiti *et al.*, 2019; Cavallo, *et al.*, 2019; Flaaen and Pierce, 2019; Handley *et al.*, 2019; Fajgelbaum *et al.*, 2020; Flaaen *et al.*, 2020). However, well before President Donald Trump took office, the US had been targeting China through its most frequently used trade barrier: antidumping (AD) duties. As shown in Figure 1, between the election of George H. W. Bush in 1988 and the end of Barack Obama's second term in 2016, the average US AD duty against China more than tripled. Over the same period, the share of Chinese imports covered by US AD duties has also dramatically increased (from 1.4% to 7.4%), as shown in Figure A-1 in the Appendix.

Figure 1

Average AD duty against China (1988-2018)



The figure plots the average duty across AD measures in force targeting China during 1988-2016 (in blue) and during the first two years of Trump's presidency in 2017-2018 (in red). Source: Authors' calculations based on an extended version of the Temporary Trade Barriers Database (Bown, 2014).

The last decades have also witnessed the emergence of global supply chains and the rise of trade in intermediate goods (e.g. Yi, 2003; Johnson and Noguera, 2012; Antràs and Chor, 2021). In a world in which production processes are fragmented across countries, the effects of tariffs can propagate along supply chains, possibly hurting producers in downstream industries.[1] Such concerns are exacerbated by the fact that protection is often targeted towards intermediate inputs.[2]

In this paper, we examine the effects of trade protection along supply chains. To this purpose, we collect detailed information on trade barriers introduced by the United States during the last decades and combine it with disaggregated US input-output data to identify industries that are directly and indirectly exposed to protection. In our main analysis, we study the effects of AD duties, the most common trade barrier used by the United States and other WTO members (Blonigen and Prusa, 2016).[3] We focus on duties applied against China, which has been by far the biggest target of US protection: since its accession to the WTO, it was named as a target country in 73% of US AD measures.

As pointed out by Trefler (1993), endogeneity poses a key challenge to identify the impact of trade policies. AD duties and other 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 foreign input suppliers can benefit US firms in downstream sectors (e.g. allowing them to purchase inputs at lower prices) and also increase input protection (e.g. making it easier for an industry that petitions for AD to provide evidence of injury). Omitting these productivity shocks would thus work against finding negative effects of tariffs along supply chains. Other potential omitted variables such as lobbying can have similar effects. Higher tariffs (e.g. on car parts or steel) can

[1]For example, it has been argued that Trump's tariffs "on bike components have raised the costs of Bicycle Corporation of America [BCA]" ... "tariffs on steel and aluminium have so disrupted markets that plans to expand BCA are on hold, costing American jobs" ("The Trouble with Putting Tariffs on Chinese Goods," *The Economist*, May 16, 2019).

[2]Bown (2018) shows that during the last few decades AD duties applied by the United States against China are increasingly skewed towards intermediate goods. He documents similar patterns when looking at measures applied by the United States against other countries, as well as measures applied by other advanced economies. In the recent trade war with China, US tariffs were also skewed towards intermediate inputs, such as primary metals and electrical equipment (Fajgelbaum *et al.*, 2020).

[3]GATT/WTO rules allow three forms of trade barriers: AD duties to defend against imports sold at "less than fair value," countervailing duties to protect against subsidized imports, and safeguard tariffs in response to import surges. AD duties are the most common measure used by the United States against China during our sample period (see Figure A-2).

hurt producers in tradable and non-tradable downstream industries (e.g. car manufacturers or construction companies), who may thus lobby against input protection.[4] These lobbying efforts may be particularly strong in declining industries, again making it harder to identify the negative effects of protection on downstream industries.

We make two main contributions to the literature on the effects of trade protection. First, we propose a new instrumental variable for AD duties. Second, combining this instrument with disaggregated input-output data, we examine the causal effects of trade barriers along supply chains.

Our instrument is the interaction between an industry's importance in political battleground states and its historical experience at filing for AD petitions. To identify the effects of trade protection, we exploit changes in the identity of swing states across electoral terms. Exposure to these political shocks varies across industries, depending on their importance across states (captured by initial employment shares) and their historical experience in the AD process (captured by pre-sample AD petitions). The logic behind our identification strategy is that AD protection should be skewed in favor of industries that are important in swing states, but only if they can exploit this political advantage thanks to their prior knowledge of the complex procedures to petition for AD duties.

Our identification strategy builds on the literature on the political economy of trade policy. Several studies show that US trade policies are biased towards the interests of swing states (e.g. Muûls and Petropoulou, 2013; Conconi *et al.*, 2017; Ma and McLaren, 2018; Fajgelbaum *et al.*, 2020).[5] We provide novel evidence that swing-state politics shapes US AD protection. We also build on the fact that, due to the legal and institutional complexity of the AD process, industries with prior experience in AD cases face lower costs of filing and a higher probability of success in new cases (Blonigen and Park, 2004; Blonigen, 2006).

We show that our instrument strongly predicts variation in AD protection (within industries across electoral terms) and is highly robust, e.g. to using different measures of AD protection, extending the analysis to all temporary trade barriers (TTBs), and employing alternative definitions of swing states. We also provide micro-level evidence supporting our instrument. First, we find that legislators from swing states are overrepresented in the

[4] For example, Gawande *et al.* (2012) report that in 2006 "[t]he steel antidumping duties in the United States were brought down partly by a coalition of otherwise rival firms. The case against the steel duties brought together rival U.S. and Japanese auto makers – General Motors Corp., Ford, and Daimler-Chrysler AG joined forces with Toyota Motor Corp., Honda Motor Co., and Nissan Motor Co.".

[5] These studies examine the effects of swing-state politics on non-tariff barriers under President Reagan (Muûls and Petropoulou, 2013), trade disputes initiated by the United States (Conconi *et al.*, 2017), US MFN tariffs (Ma and McLaren, 2018), and Trump's 2018 tariffs (Fajgelbaum *et al.*, 2020).

two most powerful committees dealing with trade policy in Congress (Finance and Ways and Means), which can affect AD decisions by exerting pressure on the International Trade Commission (ITC) through various channels (e.g. appointment confirmations, budget allocation, oversight hearings). Second, we show that our instrument is a key predictor of ITC commissioners' votes on AD and the probability of success of AD petitions.

We use our instrument to examine the effects of trade protection along supply chains, focusing on employment. We estimate two-stage least squares (2SLS) regressions in presidential term differences to identify the effects of AD duties on directly exposed and indirectly exposed industries. We show that trade protection against China reduces the growth rate of employment in downstream industries, with no significant effects in other (protected and upstream) industries. Our baseline estimates imply that a one standard deviation increase in the average input tariff faced by an industry decreases the growth rate of employment in that industry by 5.3 percentage points, explaining around 25% of the standard deviation of employment growth.

We provide evidence for the mechanisms behind the negative effects of protection along supply chains, showing that AD duties decrease imports and increase prices in protected industries, raising production costs in downstream industries. When focusing on manufacturing industries, we show that trade protection has negative effects on both production and non-production jobs in downstream industries.

Following Acemoglu *et al.* (2016), we also estimate regressions in long differences and compute the counterfactual jobs lost due to trade protection, i.e. the additional jobs that would have been created (or the jobs that would not have been destroyed) in downstream expanding (declining) industries in the absence of AD protection against China. Our estimates imply that around 2.1 million US jobs were lost in the US economy during 1992-2016. This figure corresponds to 6.6% of the 32.7 million jobs the US economy added in this period. The most negatively affected industries were large non-manufacturing sectors (e.g. construction) that rely on highly protected inputs (e.g. steel).

As mentioned before, our identification strategy is based on a shift-share research design and relies on exogenous political shocks (changes in the identity of swing states across electoral terms). Exposure to these shocks varies across industries, depending on their importance across states (captured by initial employment shares) and their historical experience in the AD process (captured by pre-sample petitions). One may be concerned about non-random exposure to the shocks. For example, industries that have more experience in AD proceedings may be more likely to be declining. Likewise, the importance of an industry in swing states may be correlated with other potential drivers of employment growth. Non-random exposure would give rise to an omitted variable bias in our 2SLS estimates, even if the political shocks are as-good-as-randomly assigned. We show that we obtain similar results when we apply the methodology proposed by Borusyak and Hull (2021) to purge our estimates from this potential bias.

One could also argue that our instrument may be picking up the effects of other policies that could be used to support industries that are important in swing states. Notice that our instrument is AD specific, since it combines an industry's importance in swing states with its prior AD petitions, implying that we only exploit variation in the political importance of an industry to the extent that this is relevant for AD protection. To further address concerns about the exclusion restriction, we control for other policies such as federal and state-level subsidies. Our 2SLS results are also robust to a battery of additional checks (e.g. including other protectionist measures and tariffs introduced during Trump's presidency).

The influential literature on the China shock pioneered by Autor *et al.* (2013) does not account for the rise in US trade protection against China, and this could bias the estimated effect of Chinese import competition on employment growth. We find that our instrument for trade protection is uncorrelated with Chinese export growth to other high-income countries, which this literature has used to instrument the growth in US imports from China. This suggests that the two instruments can be used separately to identify the employment effects of Chinese import competition and trade protection against China. When we combine them to jointly study these effects along supply chains, we confirm Acemoglu *et al.* (2016)'s finding that import competition from China generated large job losses in directly exposed and upstream industries, and show that trade protection against China caused additional job losses in downstream industries, without sheltering jobs in other industries.

Our results resonate with ongoing concerns of US businesses about the costs of protectionist measures against China. For example, in a letter sent on August 5, 2021 to Janet Yellen (Secretary of the Treasury) and Katherine Tai (United States Trade Representative), several business associations have urged the Biden administration to "mitigate the tariffs' significant and ongoing harm to the U.S. economy, U.S. workers, and U.S. national competitiveness." The letter emphasizes that protection against China exacts "a continued toll on U.S. manufacturers, service providers, and businesses. Due to the tariffs, U.S. industries face increased costs to manufacture products and provide services."[6]

The rest of the paper is structured as follows. In Section 2, we briefly review the related

[6]See `https://www.politico.com/f/?id=0000017b-4b3f-d1e7-a1fb-7bffea660000`.

literature. Section 3 provides information on the institutional procedures for the introduction of AD duties in the United States. Section 4 describes the data and variables used in our empirical analysis. In Section 5, we explain our identification strategy. Section 6 presents our empirical results on the effects of protection along supply chains. Section 7 concludes by discussing the implications of our analysis for the ongoing debates about the use of protectionist measures, especially against China, in the multilateral trading system.

2 Related Literature

Our paper is related to several streams of literature. First, it builds on the literature on the China shock, which has examined the effects of rising import competition from China on US employment (e.g. Autor *et al.*, 2013; Acemoglu *et al.*, 2016; Pierce and Schott, 2016; Wang *et al.*, 2018).[7] In particular, our paper is closely related to Acemoglu *et al.* (2016) and Wang *et al.* (2018), who estimate the employment effects of Chinese import competition in directly exposed industries and indirectly exposed downstream and upstream industries. We examine instead the impact of protection against China on employment along supply chains.

A recent stream of literature studies the effects of the US-China trade war. Amiti *et al.* (2019) examine the impact on prices and welfare. They show that tariff changes had little-to-no impact on the prices received by foreign exporters, indicating that the incidence of Trump's tariffs has fallen entirely on domestic consumers and importers.[8] Flaaen *et al.* (2020) find significant price effects due to US import restrictions on washing machines. Flaaen and Pierce (2019) find that the tariffs introduced by the Trump administration in 2018-2019 drove up the cost of inputs for American manufacturers and, combined with retaliation by trading partners, destroyed manufacturing jobs. Handley *et al.* (2019) find that Trump's tariffs disrupted firms' supply chain networks, increasing their production cost and decreasing their exports. Our analysis differs from recent studies of the US-China trade war along two main dimensions. First, rather than restricting the analysis to the Trump era, we study the effects of protection over several decades, exploiting variation in AD duties against China over time and across products. Second, we employ an instrumental variable approach to deal with the endogeneity of trade policy.

[7] Other studies have considered the effects of increased import competition from China on other outcomes, such as marriage and fertility patterns (Autor *et al.*, 2019), the polarization of US politics (Autor *et al.*, 2020a), innovation (Autor *et al.*, 2020b), and mortality (Pierce and Schott, 2020).

[8] This complete pass-through result is also supported by other studies (e.g. Cavallo *et al.*, 2019; Fajgelbaum *et al.*, 2020). Blonigen and Haynes (2002, 2010) focus on US AD duties and find pass-through rates of around 60%.

Our identification strategy is based on the findings of the literature on swing-state politics and trade policy. Muûls and Petropoulou (2013) show that states classified as swing in President Reagan's first term benefited from higher protection. Conconi *et al.* (2017) find that trade disputes initiated by the United States are more likely to involve important industries in swing states. Ma and McLaren (2018) show that swing-state politics shaped the US tariff structure at the end of the Uruguay Round. Fajgelbaum *et al.* (2020) find that the tariffs introduced by Trump in 2018 were targeted toward sectors concentrated in politically competitive counties. In this paper, we show that swing-state politics can also shape AD duties, the protectionist measure most widely used by the United States.

Our paper also contributes to the literature on trade policy and global sourcing. Various studies have emphasized the productivity-enhancing effects of importing inputs and input trade liberalization (e.g. Amiti and Konings, 2007; Goldberg *et al.*, 2010; Halpern *et al.*, 2015; Antràs *et al.*, 2017; Blaum *et al.*, 2018). Others have examined the effects of trade policy along value chains (e.g. Feinberg and Kaplan, 1993; Yi, 2003; Blanchard *et al.*, 2016; Erbahar and Zi, 2017; Conconi *et al.*, 2018; Vandenbussche and Viegelahn, 2018; Jabbour *et al.*, 2019; Barattieri and Cacciatore, 2020; Bown *et al.*, 2020; Grossman and Helpman, 2020). We contribute to this literature by using an instrumental variable strategy to study the direct and indirect effects of protection along supply chains.

Finally, our analysis is related to the literature on AD protection (for a comprehensive review, see Blonigen and Prusa, 2016). Some studies examine the direct effects of AD duties on imports from targeted countries,[9] while others consider the indirect effects on third countries.[10] A few studies examine the effects on welfare (e.g. Gallaway *et al.*, 1999) and FDI (Blonigen, 2002). To deal with the endogeneity of AD protection, some authors have combined a difference-in-differences methodology with propensity score matching (Konings and Vandenbussche, 2008; Pierce, 2011). Ours is the first paper to propose an instrumental variable for AD duties. As mentioned before, our instrument builds on the literature on the

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

[10]Prusa (1997) and Konings *et al.* (2001) focus on trade diversion, showing that AD duties targeting one country can lead to an increase in imports from non-targeted countries. Bown and Crowley (2007) show that AD measures can give rise to trade deflection (i.e. an increase in exports from targeted countries to third countries) and trade depression (i.e. a decrease in imports of the targeted country from third countries). AD can also have negative effects on aggregate trade, deterring imports from foreign firms that are not explicitly targeted. Vandenbussche and Zanardi (2010) estimate that these "chilling effects" account for about a 6% decrease in aggregate imports.

determinants of AD protection (e.g. Finger *et al.*, 1982; Bown and Crowley, 2013), and in particular on those studies that emphasize the role of AD experience (e.g. Blonigen and Park, 2004; Blonigen, 2006) and domestic political factors (e.g. Moore, 1992; Hansen and Prusa, 1997; Aquilante, 2018).

3 Antidumping in the United States

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

In the United States, AD is administrated by two agencies, each with different competences: the US Department of Commerce (DOC),[11] which is in charge of the dumping investigation, and the US International Trade Commission (ITC), which is in charge of the injury investigation. The DOC is an integral part of the US Administration, while the ITC is a bipartisan agency composed of six commissioners nominated by the President and confirmed by the Senate (with no more than three commissioners from the same party).

An AD case starts with a petition filed to the ITC and the DOC, claiming injury caused by unfairly priced products imported from a specific country.[12] US manufacturers or wholesalers, trade unions, and trade or business associations are all entitled to be petitioners, to the extent that they represent their industries. The petitioning process is highly complex, requiring petitioners to provide extremely detailed information about the case.[13]

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

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

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

Once a petition has been filed, the DOC decides whether a product is "dumped," i.e. imported at LTFV. The calculation of the dumping margin involves a complex procedure. According to the law, the DOC defines fair value as the foreign firm's price of the same good in its home country. However, this price is not always available, either because the foreign firm's sales in its home market are negligible or because the home country is a non-market economy. If this is the case, the DOC can base the calculation of the fair value on the exporting firm's price in third countries or on a constructed value based on the foreign firm's costs, when this information is provided.[14] A product is declared to be dumped if the dumping margin is above a threshold established by the DOC.

In the administration of antidumping, the ITC is in charge of the injury investigation. Under Section 201 of the Trade Act of 1974, the ITC "determines whether an article is being imported into the United States in such increased quantities as to be a substantial cause of serious injury, or the threat thereof, to the domestic industry producing an article like or directly competitive with the imported article." If the ITC finds that the relevant US industry has been materially injured, or threatened with material injury, as a result of the unfairly traded imports, an AD duty equal to the dumping margin established by the DOC is introduced.

During 1981-2018, the DOC ruled in favor of dumping in 81% of the cases, with significant variation in the proposed duty rates (the mean and maximum rates are respectively 65% and 493%, and the standard deviation is 79%). During the same period, the ITC ruled in favor of the petitioning industry in 68% of the investigations that reached the final stage.[15] Note also that AD measures are supposed to be temporary and can only be extended after the initial five-year period through an expiry review. However, Bown *et al.* (2020) show that US AD duties lasted on average for 12 years, with some measures imposed in the 1980s still in effect as of 2020.

data are available" (see Guidelines for Antidumping Duty Petitions).

[14] Article 15 of China's Protocol of Accession to the WTO allowed other WTO members to treat China as a non-market economy (NME) until December 2016. To this day, the United States has refused to grant the status of a market economy to China. Given its NME status, the DOC relies on third surrogate countries to determine the dumping margin. This results in the imposition of larger duties on Chinese products.

[15] These statistics concern the final dumping and injury investigations. The DOC and the ITC also conduct preliminary investigations (see Antidumping and Countervailing Duty Handbook for more details).

4 Data and Variables

In this section, we describe the data used in our empirical analysis and the variables we construct to study the effects of trade protection along supply chains.

4.1 Data on Input-Output Linkages

The first source of data used in our empirical analysis is the US input-output tables from the US Bureau of Economic Analysis (BEA), which we use to identify vertical linkages between industries. Following Acemoglu *et al.* (2016), we use the 1992 BEA benchmark input-output table, fixing technological linkages at the beginning of our sample period.[16] We use their concordance guide to convert 6-digit BEA industry codes into 4-digit Standard Industry Classification (SIC4) codes to be able to combine input-output tables with industry-level data. This allows us to trace upstream and downstream demand linkages between 479 manufacturing and non-manufacturing (e.g. construction, services) industries. The disaggregated nature of the US input-output tables is one of the reasons why they have been used to capture technological linkages between sectors, even in cross-country studies (e.g. Acemoglu *et al.*, 2009; Alfaro *et al.*, 2016 and 2019).

Figure A-3 in the Appendix illustrates total cost and usage shares for the 479 SIC4 j industries, focusing on the top-50 input and output industries. Among input industries, some play a key role in the US economy. For example, steel (SIC 3312) is the most important input for 82 industries (see Table A-5). We discuss our application of input-output tables in more detail below, when describing the construction of our measures of exposure to trade protection.

4.2 Data on Trade Protection

Antidumping Duties

Our main source for the trade protection data is the World Bank's Temporary Trade Barriers Database (TTBD) of Bown (2014), which we have updated to include all measures introduced by the United States to the present.

The TTBD contains detailed information on three forms of contingent protection (antidumping duties, 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

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

products under investigation. For the United States, products are identified at the 10-digit Harmonized Tariff Schedule (HTS) level (or at the 5-digit Tariff Schedule of the United States Annotated for years before 1989). Appendix A.1 details our matching procedure to link each investigation to a corresponding SIC4 code.

In our empirical analysis, we focus on AD duties introduced by the United States against China. As mentioned before (see footnote **??**), China was by far the most frequent target of US AD protection in our sample period. During the seven presidential terms covering 1988-2016, the US initiated 185 cases in which China was accused of dumping. In 74% of those cases, the US imposed measures on Chinese products.

Combining information on US AD duties with the 1992 US input-output table, we can construct measures of the direct and indirect exposure to protection along supply chains. The direct effect is simply captured by the variable

$$Direct\ Tariff\ Exposure_{j,t} = Duty_{j,t}, \tag{1}$$

where $Duty_{j,t}$ is the average AD duty across all HS6 products within a SIC4 industry. This measure captures variation in both the intensive and the extensive margin of AD protection, since the average is constructed including HS goods with zero duty.[17]

Exposure to protection by downstream industries is given by

$$Downstream\ Tariff\ Exposure_{j,t} = \sum_{i=1}^{N} \omega_{i,j} Duty_{i,t}, \tag{2}$$

where $\omega_{i,j}$ is the cost share of input i in the production of j. This measure is thus a weighted average of the tariff shocks experienced by j's suppliers. Similarly, exposure to protection by upstream industries can be defined as

$$Upstream\ Tariff\ Exposure_{j,t} = \sum_{i=1}^{N} \theta_{i,j} Duty_{i,t}, \tag{3}$$

where $\theta_{i,j}$ is the share of industry j's total sales that are used as inputs in the production of industry i. Thus (3) is a weighted average of the tariff shocks experienced by j's customers.

Notice that the variable *Direct Tariff Exposure*$_{j,t}$ is only defined for the 405 tradable

[17] AD duties often vary across exporting firms from the targeted country: those ruled to be cooperative during the investigation are imposed firm-specific duties, while others receive higher industry-wide duties. In line with previous studies (e.g. Besedes and Prusa, 2017), we use the "all others" rate to construct $Duty_{j,t}$. We show that our results are unaffected if we use the average of the firm-specific duties. This is not surprising given the high correlation between the two rates (0.7 for AD duties against China).

sectors in the economy, to which import tariffs can apply. These include 392 manufacturing industries and 13 non-manufacturing but tradable industries (e.g. agriculture and mining). By contrast, the variables $\textit{Downstream Tariff Exposure}_{j,t}$ and $\textit{Upstream Tariff Exposure}_{j,t}$ can be defined for all 479 industries in the economy.

Notice also that $\textit{Direct Tariff Exposure}_{j,t}$ captures not only the direct effects on producers of protected goods within SIC4 industry j, but also indirect effects on vertically-related producers in the same industry. Given the importance of the diagonal of the input-output matrix, these indirect effects can be large in many industries. As an example, consider industry SIC 3312 ("Blast furnaces and steel mills"), which includes 235 HS6 products. In 2001, the United States introduced an AD duty against China and other countries on hot rolled steel products, covering products under 27 different HS6 lines, all belonging to the same industry (SIC 3312). Hot rolled steel is an input in the production of other HS6 goods included in SIC 3312 that were not covered by AD duties, such as tramway rails (HS 730210).[18] The diagonal of the input-output matrix is particularly important for industry SIC 3312, so protecting some steel products could generate large downstream effects within the industry.[19]

Disentangling these effects from the direct effects of protection would require more disaggregated (product-level) input-output tables and employment data for all industries.[20]

The baseline versions of (2) and (3) are constructed using the Leontief inverse of the input--output matrix to incorporate higher-order linkages and capture both direct and indirect effects of protection along supply chains. In alternative specifications, we construct these variables using only first-order input-output linkages.

Our benchmark measures of tariff exposure are in line with previous studies on the effects of trade policy changes (e.g. Topalova, 2010; Kovak, 2013). We also construct versions of the exposure variables in which each AD duty is weighted by the corresponding import penetration ratio of the industry, to allow the effects of tariff changes to depend on the degree of import reliance (e.g. Caliendo and Parro, 2015).[21]To deal with endogeneity concerns, we

[18]See Talamini et al. (2004).

[19]The $\omega_{j,j}$ coefficient for industry SIC 3312 is 0.172. For comparison, the mean $\omega_{j,j}$ for all industries is 0.035, while the mean $\omega_{i,j}$ including the diagonal is 0.002.

[20]Cox (2021) constructs a disaggregated input-output table for the steel industry, exploiting firms' exclusion requests from Trump's Section 232 steel tariffs. Conconi *et al.* (2018) construct input-output tables at the HS6 level (see Online Appendix).

[21]For example, this alternative version of $\textit{Downstream Tariff Exposure}_{j,t}$ is given by $\sum_{i=1}^{N} \omega_{i,j} Duty_{i,t} IP_i$, where IP_i is the import penetration ratio of input industry i. We measure import penetration as $Imports_i/(Imports_i + Production_i)$. We do not subtract total exports from the denominator, since this leads to some negative IP measures, possibly reflecting inventories.

construct this ratio using data from 1991, the earliest available year for US import data. At that time, the import penetration ratio for China was extremely low (1 percent on average), and thus we compute import penetration using US imports from from all countries.

In robustness checks, we construct the exposure measures defined in (1)-(3) using the following alternative measures of AD protection: $\textit{Alternative Duty}_{j,t}$, which is the average AD duty applied in year t to imports from China across investigations in industry j, and $\textit{Product Coverage}_{j,t}$, which is the share of HS6 goods in sector j covered by AD duties against China in year t.

Table A-6 reports descriptive statistics of the tariff exposure variables constructed using the variables $\textit{Duty}_{j,t}$, $\textit{Alternative Duty}_{j,t}$, and $\textit{Product Coverage}_{j,t}$. To deal with outliers, in the empirical analysis, we winsorize (at the 5^{th} and 95^{th} percentiles) the AD variables used to construct the three tariff exposure measures. Even though our focus is on antidumping, we also use data on other TTBs (safeguards and countervailing duties), which are less commonly used than AD duties (see Figure A-2).

Other Protectionist Measures

We also use data on the US most-favored-nation (MFN) tariffs. Unlike AD duties, they are applied in a non-discriminatory manner to imports from all countries (Article I of the GATT). The source for MFN tariffs is the World Integrated Trade Solution (WITS) database. MFN tariffs emerge from long rounds of multilateral trade negotiations: at the end of each round, governments commit not to exceed certain tariff rates, and tariff bindings can only be altered in a new round of negotiations.[22]

In 2018, the Trump administration introduced tariffs on hundreds of goods under three rarely used US trade laws (Sections 201 and 301 of the Trade Act of 1974, Section 232 of the Trade Expansion Act of 1962).[23] These were stacked on top of AD duties already applying

[22] During 1988-2016, the mean applied MFN tariff was 3.4%. Within SIC4 industries, there is little variation in US MFN tariffs over time: during most of our sample period, the rates applied by the United States coincide with the tariff bindings agreed at the end of the Uruguay Round of multilateral trade negotiations (1986-1994).

[23] On February 7, the United States introduced safeguard measures on solar panels and washing machines (with duty rates of 30% and 20%, respectively) under Section 201 of the Trade Act of 1974, which permits the President to grant temporary import relief, by raising tariffs on goods entering the United States that injure or threaten to injure domestic industries. On March 23, it implemented 25% tariffs on steel and 10% tariffs on aluminum under Section 232 of the Trade Expansion Act of 1962, which gives the President authority to restrict imports in the interest of national security. On July 6, August 23, and September 24, the US implemented tariffs of 25%, 25%, and 10%, respectively, on different sets of products from China under Section 301 of the Trade Act of 1974, which gives the President authority to impose tariffs against countries that make unjustified, unreasonable, or discriminatory trade actions.

to Chinese imports. Some of Trump's tariffs have hit China exclusively, while others have hit China along with other countries. We have collected information on these additional tariffs, which covered $303.7 billion, or 12.6% of US imports in 2017 (Bown, 2019). Relative to AD duties, the special tariffs introduced by Trump vary much less across SIC4 industries. By the end of 2018, they applied to 79% of manufacturing industries; the corresponding share for AD duties applied against China in 2018 was 24%. Trump's tariffs also exhibited much less variation on the intensive margin, ranging between 10% and 25%; the corresponding range for AD duties on Chinese goods in 2018 was 8%-493%.

4.3 Other Data

In our empirical analysis, we make use of several other datasets:

- US Census County Business Patterns (CBP): we use this dataset to study the effects of input protection on employment. The CBP provides information on industry-level employment up to 2018. The variable $Employment_{j,t}$ measures total employment in SIC4 industry j in year t.

- United Nations (UN) Comtrade database: we use this dataset to measure imports and import prices. Comtrade provides information on bilateral trade flows at the HS6 level. To map trade flows in HS to a SIC4 industry, we use the crosswalk provided by Autor *et al.* (2013). Appendix A-1 provides more details about this matching procedure. The variable $Imports_{j,t}$ is the value of imports (in real 2007 dollars). The variable $Import\ Price_{j,t}$ is the average unit value of US imports from China in industry j in year t.[24]

- US Bureau of Labor Statistics (BLS): we use this dataset to measure domestic and input prices. The variable $Domestic\ Price_{j,t}$ is the producer price index (PPI) in SIC4 industry j in year t.[25] The variable $Input\ Price_{j,t}$ is the average input price faced by industry j.[26]

- NBER-CES Manufacturing Industry Database: we use this dataset to study the effects of tariffs on different types of workers. We construct the variables $Production\ Workers_{j,t}$

[24] We first construct unit values at the HS6 level in year t (using the HS1992 nomenclature). We then convert the data to the SIC4 level (using the HS1992-SIC4 concordance files), weighting the prices of HS6 products by their import values in year t.

[25] We normalize both import and domestic prices of each industry to 100 for the year 2000 to create a harmonized price index.

[26] We construct this measure by combining PPI data from the BLS with input-output data from the BEA: $Input\ Price_{j,t} = \sum_{i=1}^{N} \omega_{i,j} Domestic\ Price_{i,t}$, where $\omega_{i,j}$ is the cost share of input i in the production of j.

and *Non-Production Workers*$_{j,t}$ (number of jobs, in thousands), as well as real *Wages*$_{j,t}$ (in dollars).[27]

- Database on US subsidies: following recent studies (e.g. Slattery, 2020; Slattery and Zidar, 2020), we use information from Subsidy Tracker, which provides information on subsidies by recipient firm from more than 1,000 state, local, and federal economic programs.[28] For each subsidy (or portion of a multi-year subsidy), the dataset provides information on the recipient company (i.e. company name, headquarters location, NAICS code), the value and type of the subsidy, the year of award and the level of government (i.e. state, local, or federal) of the awarding agency. We aggregate subsidies to the industry-year level, by summing the value of subsidies across recipient companies.[29]

5 Identification Strategy

5.1 Endogeneity Concerns

The goal of our paper is to study the effects of protection along value chains, using detailed information on input-output linkages and exploiting variation in US tariffs across industries and over time. As pointed out by Trefler (1993), the endogeneity of trade policy poses a major challenge to examine the effects of tariff changes. For example, positive productivity shocks to foreign exporters, or negative productivity shocks to domestic producers, are unobservables that are related both to employment growth and trade protection. Omitting these variables from an OLS regression would cause estimates of the direct effect of protection on employment to be (negatively) biased.

When studying the impact of tariffs along supply chains, a major concern is that the results might be confounded by unobservables that are correlated both with the level of protection in upstream industries and the performance of downstream industries. One example is productivity shocks. A positive productivity shock experienced by foreign input suppliers,

[27] To deal with outliers, we winsorize these variables at the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles.

[28] These data can be found at `https://www.goodjobsfirst.org`.

[29] For our analysis, we convert the subsidy data from the NAICS classification into the SIC4 classification. We harmonize NAICS codes over time to the NAICS 1997 nomenclature, using the concordance tables provided by the United Nations Statistics Division and the procedure of Autor *et al.* (2013). We assume that NAICS codes in our data refer to the year of award of the subsidy, as NAICS code data is disclosed and reported by state and local governments. We then concord NAICS 1997 codes to SIC 1987 codes. When the NAICS code is not reported, we manually assign a SIC4 code, based on the industry name and the SIC4 description. We exclude entries for which the industry name is missing.

which allows them to lower their prices, should benefit US firms in downstream sectors. The same shock can also lead to an increase in input protection: for AD investigations, a surge in the volume of imports makes it more likely that the industry petitioning for protection passes the injury test, which largely determines whether the duties are implemented. Since this omitted variable is correlated in the same direction with both the dependent and the independent variables, the estimated OLS coefficients will suffer from a positive bias, working against finding negative effects on downstream industries.

Similar concerns are raised by other potential omitted variables, including lobbying. Higher tariffs in upstream industries can increase production costs for downstream industries. Final good producers (e.g. construction companies, car manufacturers) will thus lobby against high tariffs on their inputs (e.g. steel, car parts).[30] If these lobbying efforts are more pronounced in declining industries, the estimated OLS coefficients would again have a positive bias.

5.2 A New Instrument for Antidumping Protection

To deal with endogeneity concerns, we follow an instrumental variable (IV) approach. The logic of our identification strategy is that variation in AD duties should depend on politicians' incentives to favor key industries in swing states and on industries' ability to petition for AD protection.

Our instrument is defined as follows:

$$IV_{j,T} = \textit{Swing Industry}_{j,T} \times \textit{AD Experience}_{j}. \tag{4}$$

The first component of the instrument, $\textit{Swing Industry}_{j,T}$, captures exogenous variation in the political importance of industries driven by swing-state politics. It builds on the idea that politicians have incentives to use trade policy to favor important industries in swing states (e.g. Muûls and Petropoulou, 2013; Conconi *et al.*, 2017; Ma and McLaren, 2018; Fajgelbaum *et al.*, 2020). The variable $\textit{Swing Industry}_{j,T}$ measures the importance of industry j in states classified as swing during presidential term T. In Section 5.2.1, we describe in detail the construction of this variable.

The second component of the instrument, $\textit{AD Experience}_{j}$, captures exogeneous variation in the ability of different industries to petition for AD protection. It exploits the fact that, due

[30] The literature on political economy of trade policy shows that this type of lobbying is at work (e.g. Gawande *et al.*, 2012; Mayda *et al.*, 2018).

to the legal and institutional complexity of the AD process, industries with prior experience in AD cases face lower costs of filing and a higher probability of success in new cases (Blonigen and Park, 2004; Blonigen, 2006). The variable $\textit{AD Experience}_j$ measures the historical experience of industry j at filing petitions for AD duties. In Section 5.2.2, we provide more details about the construction of this variable.

Our identification strategy is based on a shift-share research design, which studies the impact of a set of shocks (or "shifters") on units differentially exposed to them, with the exposure measured by a set of disaggregate weights (or "shares").[31] In our setting, the shocks are driven by changes in the identity of swing states, which generate variation in $IV_{j,T}$ across electoral terms.

We assume that the identity of swing states is exogenous in our setting, i.e. trade policy does not affect whether the difference in vote shares between the Democratic and Republican candidates is below a certain threshold. As discussed below, we use the standard retrospective definition of swing states, which is based on vote shares in the previous presidential elections, to alleviate concerns about the validity of this assumption. In Appendix A-2, we verify that state-level exposure to AD protection during a presidential term has no significant effect on the identity of swing states at the end of that term. We also show that the extent to which a state is exposed to import competition (from all countries or from China) is not correlated with whether or not the state is classified as swing.

Exposure to the political shocks varies across industries, depending on their importance across states (captured by initial employment shares) and their historical experience in the AD process (captured by pre-sample AD petitions). When studying the effects of trade protection along supply chains, exposure depends on the input-output shares defined in equations (2) and (3). All measures of exposure are constructed using information at the start of our sample period and are assumed to be exogeneous conditional on industry fixed effects, which are included in our 2SLS regressions to capture industry characteristics that might be correlated with exposure shares. Still, non-random exposure to shocks can generate an omitted variable bias. To deal with this concern, we show that our 2SLS estimates are robust to applying the "recentering" methodology proposed by Borusyak and Hull (2021).

As discussed in Section 5.3, combining the two components of the instrument is key to predicting AD protection: by themselves, $\textit{Swing Industry}_{j,T}$ and $\textit{AD Experience}_j$ cannot explain the observed variation in AD duties. Combining the two components also helps to

[31] See Bartik (1991) for an early application of this research design and Adão *et al.* (2020), Goldsmith-Pinkham *et al.* (2020), Borusyak and Hull (2021), and Borusyak *et al.* (2021) for recent contributions on the statistical properties of shift-share instruments.

alleviate concerns about the exclusion restriction. To obtain a consistent estimate of the causal impact of antidumping, our proposed instrumental variable should be uncorrelated with any other determinant of the dependent variable (Angrist and Pischke, 2009). One may be concerned that $\textit{Swing Industry}_{j,T}$ could pick up the effects of other policies that could be used to favor important industries in swing states. Given that our instrument is the interaction between $\textit{Swing Industry}_{j,T}$ and $\textit{AD Experience}_j$, it only exploits variation in the political importance of an industry to the extent that this is relevant for AD protection.[32] Moreover, in our 2SLS regressions, we always control for changes in $\textit{Swing Industry}_{j,T}$ — and the corresponding changes along supply chains — to account for possible effects of other policies. Finally, we show that the results are robust to controlling for federal and state-level subsidies.

5.2.1 $\textit{Swing Industry}_{j,T}$

The first component of our instrument exploits exogeneous variation in the political importance of industries driven by swing-state politics in the United States. In US presidential elections, voters do not directly choose the executive, they vote for their state's representatives in the Electoral College, who then vote for the president. The winner-takes-all nature of the Electoral College implies that candidates can count some states as "safe," comfortably in the hands of their party. The states that really matter are the "swing" or "battleground" states, in which a few thousand or even a few hundred votes can shift the entire pot of electors from one candidate to the other. As mentioned in Section 2, several studies (e.g. Muûls and Petropoulou, 2013; Conconi *et al.*, 2017; Ma and McLaren, 2018; Fajgelbaum *et al.*, 2020) show that US trade policies are biased towards the interests of swing states.[33]

To define swing states, we use information on the difference in vote shares of Democratic and Republican candidates in the previous presidential election, in line with the literature. In particular, the dummy variable $\textit{Swing State}_{s,T}$ classifies a state s to be swing during a presidential term T if the difference in the vote shares of the candidates of the two main parties in the previous presidential election was less than 5%. In robustness checks, we use

[32] Our instrument predicts no AD protection for industries that are important in swing states (high $\textit{Swing Industry}_{j,T}$) but cannot exploit this political advantage due to their lack of AD experience ($\textit{AD Experience}_j = 0$).

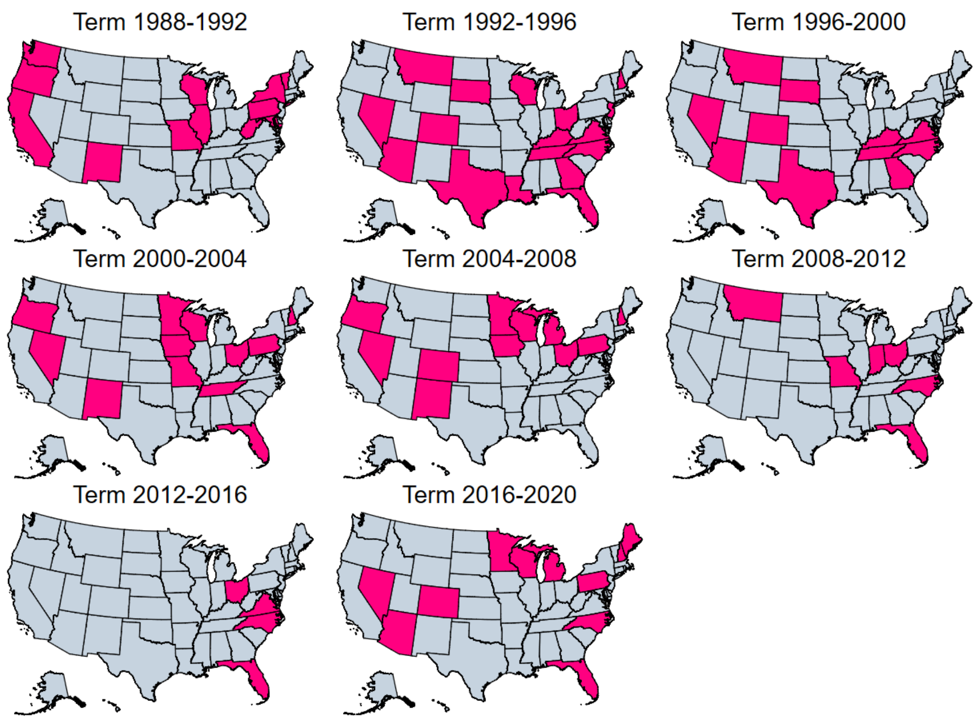
[33] The argument that US politicians use trade policy to favor the interests of swing states is also often heard in the media. For example, an article in the *Guardian* pointed out that in a letter to Pascal Lamy (Europe's former top trade negotiator), Stephen Byers (former UK secretary of state for trade and industry) wrote that the 2002 US steel tariffs were introduced by President George W. Bush "to gain votes in key states like West Virginia, Ohio, Pennsylvania and Michigan where the steel industry is a major employer" ("Blair ally in poll threat to Bush," *The Guardian*, November 17, 2003).

alternative definitions of swing states.

Figure 2 illustrates the states classified as swing during the last eight presidential terms, based on the difference in vote shares in the previous presidential elections. During our sample period, 32 states were classified as swing, some multiple times.

Figure 2

Swing states during the last eight presidential terms



The maps indicate in pink the states classified as swing (less than 5% difference in the vote shares of Democratic and Republican candidates) during the last eight presidential terms, based on the previous presidential elections.

Our identification strategy relies on changes in the identity of swing states across terms. For example, the dummy variable $Swing\ State_{s,T}$ changed five times for Missouri during our sample period (in 1992, 2000, 2004, 2008, 2012). In robustness checks, we randomize the identity of swing states to create an "expected" instrument, as suggested by Borusyak and Hull (2021).

To capture heterogeneity in the geographical distribution of industries, we use CBP data on state-level employment shares. To dispel the concern that these shares might be affected by trade protection, we use data from 1988, the first year of our sample period.[34] To measure

[34]Using data from later years would yield very similar results, given that the geographical distribution of industries across states is stable over time. This can be seen in Figure A-4, which plots state-level employment shares by SIC4 industry in 1988 and 2011, using data from Acemoglu *et al.* (2016). The correlation between the shares in these two years is 0.96.

the importance of an industry j in states classified as swing during a presidential term T, we construct the following variable:

$$\textit{Swing Industry}_{j,T} = \frac{\sum_s L_{s,j}^{1988} \times \textit{Swing State}_{s,T}}{\sum_s \sum_j L_{s,j}^{1988} \times \textit{Swing State}_{s,T}}. \tag{5}$$

This is the ratio of the total number of workers employed in industry j in states that are classified as swing during electoral term T, over total employment in swing states.[35]

The variable $\textit{Swing Industry}_{j,T}$ captures exogenous variation in the political importance of an industry. It exploits changes in the importance of states across electoral terms driven by swing-state politics ($\textit{Swing State}_{s,T}$) and differences in the importance of industries across states, driven by the initial employment shares ($L_{s,j}^{1988}$).[36] Table A-7 shows descriptive statistics of this variable, and the top panel of A-8 lists the top-10 industries ranked by $\textit{Swing Industry}_{j,T}$ in our sample.

Swing-state politics can shape AD protection by affecting the decisions of the DOC and the ITC, the two key institutions involved in AD policy in the United States. As explained in Section 3, the DOC determines whether a product has been sold at "less than fair value" and computes the "dumping margin," while the ITC determines whether this "unfair practice" has caused material injury to the US industry. Political considerations can directly affect decisions of the DOC, which is part of the executive branch. Through various political appointments, the White House can shape AD decisions of the DOC.[37] In some cases, the executive directly intervenes in these decisions.[38]

Swing-state politics can also affect AD decisions of ITC commissioners. Previous studies show that these commissioners are not independent "bureaucrats." In particular, ITC votes

[35] We construct $\textit{Swing Industry}_{j,T}$ based on employment in all tradable sectors (those that can receive AD protection). In robustness checks, we define the variable over the total number of workers in all sectors.

[36] Using data on state-level employment shares also allows us to compare the location of industries based on their position in the supply chain. This reveals that final good industries are more geographically dispersed than input industries: 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). Figure A-5 in the Appendix illustrates the geographical distribution across US states of two industries: SIC 3312 ("Blast furnaces and steel mills") and SIC 1510 ("Construction").

[37] In the current organizational chart, the President nominates the top positions (Secretary, Deputy Secretary), as well as the key positions in charge of AD (e.g. Under Secretary for International Trade, Assistant Secretary for Market Access and Compliance). These appointees must be confirmed by the Senate. Several lower-ranked positions involved in AD decisions (e.g. Deputy Assistant Secretary for Enforcement and Compliance) are usually politically appointed, but do not require confirmation by the Senate.

[38] For example, in 2017 the DOC reversed its prior negative position on an AD case involving imports from Korea of oil country tubular goods, a type of steel product used in oil fields, after Peter Navarro, Director of the National Trade Council under Trump, sent a "Recommendation for Action" letter requesting a minimum 36% import duty (see US Court of International Trade, Consol. Court No. 17-00091).

on AD reflect the interests of the members of the two most powerful committees dealing with trade policy in Congress: the Finance committee in the Senate and the Ways and Means committee in the House.[39] In Appendix A-3, we provide novel evidence that swing-state politics influences AD decisions. First, we find that legislators from swing states are over-represented in the Finance and Ways and Means congressional committees, which can affect decisions on AD by putting pressure on ITC commissioners through various channels (e.g. appointment confirmations, budget allocation, oversight hearings). More importantly, we show that our instrument is a key predictor of ITC commissioners' votes and the probability of success of AD petitions.

5.2.2 $\textit{AD Experience}_j$

As explained in Section 3, AD investigations in the United States begin with a petition by a domestic party, usually a group of producers competing with the imported product that is allegedly dumped. The DOC and the ITC then conduct investigations to determine whether there is dumping and whether this "unfair trade" practice is injuring the domestic industry represented by the petitioners. If these criteria are satisfied, an AD duty equal to the dumping margin calculated by the DOC is applied to the imported product.

As pointed out by Blonigen (2006), the process to petition for AD duties is extremely complex (see also footnote 13): "the petitioning party must present the AD authorities with a reasonable petition that presents their case for the investigation and then provide substantial information, as well as legal analysis and arguments, during the course of the investigation. The legal details, as well as the practical issues of how government agencies apply the law, are substantial" (p. 716). As a result of this complexity, prior experience by petitioning parties plays an important role in AD filings and outcomes. Blonigen shows that previous experience lowers future filing costs and increases petitioners' effectiveness in arguing their case, generating higher probabilities of favorable outcomes.

Following this idea, we use information on AD petitions filed by US industries during our pre-sample period to construct a measure of an industry's ability to obtain protection. During the 1980s, legal and institutional changes in AD proceedings made it easier to file for AD protection, which led to a steep increase in the number of AD petitions (see Irwin,

[39] Moore (1992) finds that ITC commissioners are more likely to favor AD petitions involving the constituencies of Finance committee members. Hansen and Prusa (1997) show that the ITC is more likely to support petitions filed by industries with representatives in the Ways and Means committee. Aquilante (2018) emphasizes the role of party politics, showing that ITC commissioners appointed by the Democratic (Republican) party are more likely to vote in favor of AD when the petitioning industry is key (in terms of employment) in the states represented by Democratic (Republican) senators in the Finance committee.

2005 and 2017). Our experience variable is the count of AD petitions filed by industry j in 1980-1987:

$$AD\ Experience_j = \sum_{t=1980}^{1987} AD\ Petitions_{j,t}. \tag{6}$$

This variable captures exogenous variation in industries' ability to petition for AD protection, coming from their historical (pre-sample) knowledge of AD procedures. To ensure exogeneity of the instrument, we exclude petitions targeting China and leading to measures in force after 1987.

The variable $AD\ Experience_j$ is positive for 43% of tradable industries. Descriptive statistics of the variable $AD\ Experience_{j,t}$ are reported in Table A-7. There is significant cross-sectoral variation in the number of AD cases initiated during this period (the variable $AD\ Experience_j$ has a mean of 1 and a standard deviation of 3), possibly due to the fact that some industries did not need to file for AD, since they were already protected by other policies (e.g. voluntary export restraints, the Multi-Fibre Arrangement). The bottom panel of Table A-8 lists the top-10 SIC4 sectors with the highest value of $AD\ Experience_j$ during 1980-1987.[40]

In line with Blonigen (2006), we find that the number of petitions filed by an industry depends crucially on its previous experience: the correlation between the number of petitions filed by SIC4 industry j in 1988-2016 and $AD\ Experience_j$ is 0.88.[41]

5.3 Predicting AD Protection

In this section, we show that our IV strategy allows us to predict AD protection. Since our instrument varies at the presidential-term level, we consider four-year terms as the time dimension of the panel and estimate the following regression by ordinary least squares (OLS):

$$Duty_{j,T} = \beta_0 + \beta_1 IV_{j,T} + \delta_j + \delta_T + \varepsilon_{j,T}, \tag{7}$$

[40] The highest number of petitions (48) was filed by the steel industry (SIC 3312). In robustness checks, we verify that our results continue to hold if we exclude steel from our sample.

[41] Blonigen (2006) finds that prior AD experience is also associated with lower dumping margins and interprets this result as suggesting that experience lowers filing costs, leading to the filing of weaker cases. In our data, we find no evidence that more experienced industries file weaker cases: the correlation between $AD\ Experience_j$ and the average dumping margin of cases filed by industry j is 0.04 and not statistically significant.

where $Duty_{j,T}$ measures the average AD duty on imports from China in SIC4 industry j in force at the end of term T. We include sector fixed effects (δ_j) defined at the SIC4 level to account for time-invariant sector characteristics that may affect the level of protection, as well as term fixed effects (δ_T) to control for general macroeconomic and political conditions. In line with earlier studies (e.g. Acemoglu *et al.*, 2016; Pierce and Schott, 2016), we weight regression estimates by start-of-period (1988) industry employment.[42] We cluster standard errors at the SIC3 level (221 industries) to allow for correlated industry shocks.

The results of estimating regression (7) are reported in column 1 of Table 1. The dependent variable is our baseline measure of AD protection against China ($Duty_{j,T}$). The coefficient of $IV_{j,T}$ is positive and significant at the 1% level, indicating that our instrument is a good predictor of the level of AD protection granted to a SIC4 industry during an electoral term. More specifically, we find that a one standard deviation (0.110) increase in our IV increases AD duties by 1.5 percentage points, which explains 44% of the standard deviation of $Duty_{j,T}$ in 1988-2016.

Table 1

Predicting AD protection

	(1)	(2)	(3)
$IV_{j,T}$	0.137***		0.141***
	(0.028)		(0.025)
$Swing\ Industry_{j,T}$		0.767	-0.086
		(0.475)	(0.285)
SIC4 FE	Yes	Yes	Yes
Term FE	Yes	Yes	Yes
Adjusted R^2	0.56	0.53	0.56
Observations	2,835	2,835	2,835

The table reports OLS estimates. The dependent variable is $Duty_{j,T}$, the average AD duty on imports from China in SIC4 industry j in force at the end of term T. $IV_{j,T}$ is defined in equation (4). The sample covers 1988-2016. Observations are weighted by 1988 employment. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Combining the two components of the instrument is key to predicting AD protection. Notice that $AD\ Experience_j$ is time invariant (and captured by SIC4 fixed effects), and thus cannot explain within-industry variation in $Duty_{j,T}$ across electoral terms. Similarly, the variable $Swing\ Industry_{j,T}$ cannot by itself explain changes in AD protection. This can be seen by comparing the results in columns 2 and 3 of Table 1, in which we regress $Duty_{j,T}$ on

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

Swing Industry$_{j,T}$, first by itself and then with $IV_{j,T}$. The coefficients of *Swing Industry*$_{j,T}$ are not statistically significant, while the coefficient of $IV_{j,T}$ remains significant at the 1% level (and very similar to the coefficient reported in column 1). These results confirm that politically important industries benefit from higher protection, but only if they have long-term knowledge of the complex procedures to petition for AD duties.

In line with this idea, sectors such as "Motor vehicle parts and accessories" (SIC 3714) and "Blast furnaces and steel mills" (SIC 3312), which are often politically important (high average *Swing Industry*$_{j,T}$) and are experienced in filing for AD in the 1980s (high *AD Experience*$_j$), receive high levels of protection. By contrast, industries with high average *Swing Industry*$_{j,T}$ but no prior experience in AD filings receive little or no AD protection. This is the case, for example, for "Search and navigation equipment" (SIC 3812).

We carry out a series of additional estimations to verify the robustness of our instrument. In Table 2, we use alternative measures of AD protection when estimating (7).[43] In columns 1-2, we use the alternative measures defined in Section 4.2 (*Alternative Duty*$_{j,T}$, *Product Coverage*$_{j,T}$). In column 3, we include all TTBs (AD, countervailing duties, safeguards) applied against China.[44] In column 4, we construct the variable *Duty*$_{j,T}$ as the average of the firm-specific duties instead of the "all others" rate. Finally, in column 5 we exclude steel, the industry with the highest average $IV_{j,T}$ during our sample period. The estimated coefficient of $IV_{j,T}$ remains positive and significant in all specifications.[45]

Table 2

Predicting AD protection (alternative AD measures)

	Alternative duty (1)	Product coverage (2)	All TTBs (3)	Firm-specific duty (4)	No steel (5)
$IV_{j,T}$	1.383***	10.484***	0.135***	0.051***	0.186**
	(0.271)	(1.721)	(0.028)	(0.013)	(0.077)
Adjusted R^2	0.56	0.58	0.57	0.58	0.54
Observations	2,835	2,835	2,835	2,835	2,828

The table reports OLS estimates. In columns 1-2, the dependent variable is *Alternative Duty*$_{j,T}$ and *Product Coverage*$_{j,T}$, respectively. In column 3, we include all TTBs (AD duties, countervailing duties, and safeguards). In column 4, the dependent variable is the average of firm-specific AD duties. In column 5, we exclude the steel industry (SIC 3312). $IV_{j,T}$ is defined in equation (4). The sample covers 1988-2016. Observations are weighted by 1988 employment. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

[43] The coefficient of $IV_{j,T}$ is unaffected if we also include *Swing Industry*$_{j,T}$.

[44] Countervailing duties on China are almost always applied in combination with antidumping duties.

[45] Our analysis focuses on China, which was by far the most frequent target of AD. We have also constructed the measure *Duty*$_{j,T}$ as a weighted average of the duties applied to the top 10 target countries or the top 10 exporters to the United States (with the weights being the shares of imports from the target/exporting country in the year before the investigation). The results (available on request) are robust to using this measure when estimating (7).

A second set of robustness checks, which are reported in Table 3, is related to our instrument. In columns 1-3, we consider alternative definitions of swing states to construct $IV_{j,T}$. The variable *Swing Industry*$_{j,T}$ defined in equation (5) already takes into account differences in the size of swing states with respect to their workforce. In column 1, we weight the dummy variable *Swing State*$_{s,T}$ by the number of electoral votes assigned to each swing state s in term T.[46] In our baseline estimations, we follow the literature in classifying a state to be swing if the difference in vote shares of the candidates from two main political parties in the previous presidential elections is less than 5%. In column 2, we increase the threshold to 10%. This definition leads us to classify many more states as swing (22 on average), decreasing the accuracy of our instrument.[47]

Table 3

Predicting AD protection (alternative measures of $IV_{j,T}$)

	Electoral votes (1)	10% threshold (2)	Next elections (3)	Alternative Swing Industry (4)	Alternative Experience (5)
$IV_{i,T}$	0.114***	0.207**	0.082***	0.548***	0.107***
	(0.021)	(0.103)	(0.025)	(0.108)	(0.023)
SIC4 FE	Yes	Yes	Yes	Yes	Yes
Term FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.56	0.53	0.54	0.56	0.56
Observations	2,835	2,835	2,835	2,835	2,835

The table reports OLS estimates. The dependent variable is *Duty*$_{j,T}$, the average AD duty on imports from China in SIC4 industry j in force at the end of term T. $IV_{j,T}$ is defined in equation (4). In column 1, the variable *Swing Industry*$_{j,T}$ used to construct $IV_{j,T}$ is constructed weighting each swing state by its number of electors. In column 2, swing states are defined based on the outcome of the previous presidential elections (10% difference in vote shares between the Democratic and Republican candidates), while in column 3 they are defined on the outcome of the next presidential elections (5% difference in vote shares). In column 4, we use an alternative definition of the variable *Swing Industry*$_{j,T}$ (based on total employment in swing states). In column 5, we use an alternative definition of *AD Experience*$_j$ (which accounts for all petitions in 1980-1987) to construct $IV_{j,T}$. The sample covers 1988-2016. Observations are weighted by 1988 employment. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Our retrospective definition ensures that the identity of swing states is not affected by trade policy, but does not take into account new information that politicians may acquire

[46]The Electoral College is a body of electors established by the US Constitution, which forms every four years to elect the president and vice president of the United States. It consists of 538 electors, and an absolute majority of electoral votes (270 or more) is required to win the election. Data on the number of electors come from Dave Leip's Atlas of U.S. Presidential Elections.

[47]For example, using this definition, California is classified as swing in the 2004 presidential elections, given that the difference in vote shares in the state was 9.9%. We have also tried to use a threshold of 2.5%, which produced an insignificant coefficient. This is not surprising given that this lower threshold can lead us to mistakenly classify several states as "safe." For example, in the 2008 presidential elections, the differences in vote shares in the battleground states Ohio and Florida were respectively 4.6% and 2.8%, and thus they are excluded from the set of swing states when one uses the restrictive 2.5% threshold.

during a term on the identity of battleground states in the next elections. In column 3, we keep the standard 5% threshold, but define swing states based on the outcome of the next presidential elections. Our baseline definition of $\textit{Swing Industry}_{j,T}$ is the ratio of total employment in industry j in states classified as swing during term T, over total employment in those states in tradable industries. In column 4, we construct our instrument using an alternative definition of $\textit{Swing Industry}_{j,T}$, based on employment in all industries. Finally, in column 5 we use a different definition of $\textit{AD Experience}_j$ to construct $IV_{j,T}$. Recall that our baseline definition excludes all AD petitions targeting China and leading to measures in force during our sample period. In column 5, we include petitions leading to measures in force after 1987 (but still excluding petitions targeting China). Across all specifications, the coefficient of $IV_{j,T}$ is positive and significant, confirming that our instrument is a strong predictor of AD protection.[48]

6 The Effects of Protection Along Supply Chains

6.1 Main Results

The goal of our analysis is to identify the impact of protection along supply chains. To this purpose, we exploit time-series and cross-sectional variation in AD protection against China during the seven presidential terms covering 1988-2016. In line with previous studies on the China syndrome (e.g. Autor *et al.*, 2013; Acemoglu *et al.*, 2016; Pierce and Schott, 2016), our main focus is on employment.

We first study the direct effects of protection, estimating the following 2SLS regressions in differences:[49]

$$\Delta L_{j,T} = \beta_0 + \beta_1 \, \Delta \textit{Direct Tariff Exposure}_{j,T} + \beta_2 \, \Delta \textit{Swing Industry}_{j,T} + \delta_j + \delta_T + \varepsilon_{j,T}. \tag{8}$$

The dependent variable $\Delta L_{j,T}$ is the growth rate of employment in SIC4 industry j during term T.[50] The key variable of interest is $\Delta \textit{Direct Tariff Exposure}_{j,T}$, the change in the AD duty applied to Chinese imports of industry j during term T, instrumented by $\Delta IV_{j,T} =$

[48]Unlike other trade policies (e.g. safeguards or the initiation of trade disputes), AD is not directly controlled by the executive. Still, whether the president can be re-elected or is a "lame duck" may affect the power of our instrument. If we estimate (7) separately to predict AD measures during first and second terms, the coefficients of $IV_{j,T}$ are positive and significant in both samples (available on request).

[49]Estimating regressions in differences rather than levels allows us to control for sectoral trends and thus account for other determinants of employment growth.

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

$AD\ Experience_j \times \Delta Swing\ Industry_{j,T}$. Note that variation in $\Delta Direct\ Tariff\ Exposure_{j,T}$ comes not only from newly imposed AD duties, but also the expiry of pre-existing ones. The variable $\Delta Swing\ Industry_{j,T}$ accounts for the effects of other policies that may be used to favor important industries in swing states. The industry fixed effects at the SIC4 level (δ_j) control for time-invariant industry characteristics (including $Experience_j$), as as well as (linear) sectoral trends that may affect employment growth.[51] The inclusion of term fixed effects (δ_T) allows us to control for macroeconomic and political conditions. We weight observations by start-of-period industry employment, and cluster standard errors at the SIC3 level to allow for correlated industry shocks.

It should be stressed that our 2SLS estimates capture local average treatment effects, i.e. the effect of the treatment ($IV_{i,T}$) for the "compliers," the subset of the sample that takes the treatment if and only if they were assigned to it (Imbens and Angrist, 1994). We are thus capturing the effects of politically-driven protectionist measures identified by our instrument.

The results of estimating (8) are reported in column 1 of Table 4.[52] The coefficient of $\Delta Direct\ Tariff\ Exposure_{j,T}$ is not significant. This is not surprising: as discussed in Section 4.2, this variable captures not only the direct effects of AD duties on producers of protected goods within SIC4 industry j, but also the indirect effects on vertically-related producers in the same industry.[53] Although the net employment effect of AD duties in protected industries is not significant, there could be some job gains within these industries. Identifying these gains would require product-level employment and input-output data.

The last row of Table 4 reports the Kleibergen-Paap (KP) F-statistics, which indicate that we can reject the hypothesis that our instrument is weak.[54] In column 1 of Table A-9 in the Appendix, we report the first-stage results of the 2SLS regressions corresponding to column 1 of Table 4. The coefficient of our instrument is positive and significant at the 1% level. In column 2 of the same table, we report the corresponding reduced-form results.

[51] As discussed in Section 6.2, the results are robust to using broader or no industry fixed effects.

[52] Throughout Table 4, we report the coefficients of the tariff exposure measures, omitting the coefficients of the additional controls included in the regressions for expositional clarity.

[53] Going back to the example of AD duties on hot rolled steel, they may have positive effects on producers of this type of steel, but negative effects on other producers within SIC 3312 that use hot rolled steel as an input (e.g. tramway rails). We would expect positive effects of protection for industries in which the indirect effects are limited. Indeed, if we include in (8) an interaction between $\Delta Direct\ Tariff\ Exposure_{j,T}$ and a dummy variable identifying industries in which the diagonal of the input-output matrix is higher than the median (0.012), the coefficient of $\Delta Direct\ Tariff\ Exposure_{j,T}$ is positive and significant, while its sum with the interaction term is not significant.

[54] The KP statistic is a version of the Cragg-Donald statistic adjusted for clustered robust standard errors. The statistics in Table 4 are all above the critical value of 16 (with one endogenous variable) and 7 (with two endogenous variables) based on a 10% maximal IV size.

Table 4

The impact of protection on employment along supply chains

	Tradable sectors		All sectors	
	(1)	(2)	(3)	(4)
Δ*Direct Tariff Exposure*$_{j,T}$	-0.162	-1.014		
	(1.458)	(1.529)		
Δ*Downstream Tariff Exposure*$_{j,T}$		-22.396***	-28.716***	-26.496***
		(6.139)	(7.406)	(6.535)
Δ*Upstream Tariff Exposure*$_{j,T}$		1.292	-0.894	1.807
		(5.267)	(6.119)	(5.537)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,833	2,833	3,351	3,351
KP F-statistic	26.5	7.60	66.2	89.9

The table reports the 2SLS estimates. The dependent variable $\Delta L_{j,T}$ is the log change in employment in SIC4 industry j during term T. The tariff variables capture changes in the exposure to AD protection, as measured by (1)-(3), instrumented using changes in the corresponding IV variables. Δ*Downstream Tariff Exposure*$_{j,T}$ and Δ*Upstream Tariff Exposure*$_{j,T}$ are constructed incorporating higher-order input-output linkages. In columns 2-3 (column 4), we exclude (include) the diagonal of the input-output matrix. The coefficients of the direct and indirect Δ*Swing Industry* variables included in (8)-(10) are not reported. The sample covers 1988-2016. In columns 1 and 2 (3 and 4), it comprises tradable sectors (all sectors). Observations are weighted by 1988 employment. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Next, we jointly examine the effects of AD duties on directly and indirectly exposed industries:

$$\begin{aligned}\Delta L_{j,T} \quad = \quad & \beta_0 + \beta_1 \Delta \textit{Direct Tariff Exposure}_{j,T} + \beta_2 \Delta \textit{Downstream Tariff Exposure}_{j,T} \\ & + \beta_3 \Delta \textit{Upstream Tariff Exposure}_{j,T} + \gamma \Delta \textit{Swing}_{j,T} + \delta_j + \delta_T + \varepsilon_{j,T}, \qquad (9)\end{aligned}$$

where Δ*Downstream Tariff Exposure*$_{j,T}$ and Δ*Upstream Tariff Exposure*$_{j,T}$ are the changes in exposure to AD protection for vertically-related industries, as defined in (2) and (3), instrumented by the corresponding IV measures. When estimating specification (9), we exclude the diagonal of the input-output matrix ($\omega_{j,j}$ and $\theta_{j,j}$) in the construction of downstream and upstream exposure measures. $\Delta Swing_{j,T}$ is a vector of the changes in the *Swing Industry* variables to account for the effects of other policies that could be used to support import industries in swing states.[55]

The results of estimating (9) are reported in column 2 of Table 4. The estimated β_2 coefficient is negative and significant, indicating that AD protection decreases the growth

[55] This vector includes the variables Δ*Swing Industry*$_{j,T}$, Δ*Downstream Swing Industry*$_{j,T}$, and Δ*Upstream Swing Industry*$_{j,T}$, constructed in the same way as the corresponding tariff exposure variables.

rate of employment in downstream industries. We find no significant effect on protected and upstream industries.

Specifications (8) and (9) include the variable $\Delta Direct\ Tariff\ Exposure_{j,T}$ and thus force us to limit the analysis to tradable industries. To study the effects on all industries, we estimate:

$$\begin{aligned}\Delta L_{j,T} \quad = \quad & \beta_0 + \beta_1 \Delta Downstream\ Tariff\ Exposure_{j,T} + \beta_2 \Delta Upstream\ Tariff\ Exposure_{j,T} \\ & + \gamma \Delta Swing_{j,T} + \delta_j + \delta_T + \varepsilon_{j,T}. \end{aligned} \tag{10}$$

The results of estimating specification (10) are reported in the last two columns of Table 4. In column 3, we exclude the diagonal of the input-output matrix in the construction of $\Delta Downstream\ Tariff\ Exposure_{j,T}$ and $\Delta Upstream\ Tariff\ Exposure_{j,T}$. In column 4, we include the diagonal. This is our preferred specification since it accounts for the overall impact of protection along supply chains, including protected and vertically-related industries. In both specifications, the estimated β_1 coefficient is negative and significant, confirming that AD protection reduces employment growth in downstream industries.

In terms of magnitude, the baseline estimates in column 4 of Table 4 imply that a one standard deviation (0.002) increase in predicted $\Delta Downstream\ Tariff\ Exposure_{j,T}$ decreases the growth rate of employment by 5.3 percentage points, explaining 24.6% of the standard deviation of employment growth.

It is useful to compare the 2SLS results of Table 4 with the corresponding OLS results reported in Table A-10. Notice that the coefficient of $\Delta Downstream\ Tariff\ Exposure_{j,T}$ is only significant in two of the three specifications and is much smaller in size (-3.380 instead of -26.496 in column 4) when we ignore the endogeneity of trade policy. In line with the discussion in Section 5.1, these results suggest that omitted variables generate a positive bias in the OLS estimates, which substantially underestimate the negative effects of protection on downstream industries.

In Table A-11, we reproduce Table 4 using the measures of tariff exposure weighted by import penetration, to capture the extent to which the United States relies on imports of the protected products.[56] A few remarks are in order. First, the results are qualitatively similar: AD protection has a negative impact on employment in downstream industries, but no effects in other industries. Second, import penetration can only be measured for manufacturing industries, due to the lack of data on domestic production for other tradable

[56]Weighing tariffs by import penetration rates is in line with theoretical mechanisms that emphasize differential reliance on foreign imports (e.g. Caliendo and Parro, 2015). When using the IP-weighted tariff exposure measures, we divide the coefficients by 100 for expositional clarity.

industries. This explains the lower number of observations in columns 1 and 2 of Table A-11 compared to the corresponding specifications of Table 4. Even when including all industries in columns 3 and 4, we cannot account for the effects of all protectionist measures (e.g. we cannot include AD duties on agricultural products). In line with previous studies (e.g. Topalova, 2010; Kovak, 2013), we thus keep the unweighted tariff exposure measures as our benchmark.

In Table A-12, we reproduce the benchmark specification of column 4 of Table 4 using alternative measures of AD protection. In columns 1 and 2, we use *Alternative Duty*$_{i,T}$ and *Product Coverage*$_{i,T}$. In column 3, we include all TTBs (AD duties, countervailing duties, safeguards) against China. In column 4, we construct the tariff exposure variables using only first-order input-output linkages. In all specifications, the coefficient of Δ*Downstream Tariff Exposure*$_{j,T}$ is negative and significant at the 1% level, confirming that input protection decreases employment growth in downstream industries.

The results discussed above are based on 2SLS regressions estimated in term differences (since our instrument varies at the presidential term level). To allow for long-run effects of protection, similarly to Acemoglu *et al.* (2016), we divide our sample period in three sub-periods of equal length (1992-2000, 2000-2008, 2008-2016) and estimate (8), replacing term fixed effects with period fixed effects. The results reported in column 1 of Table A-13 confirm that AD duties have no significant impact on the growth rate of employment in protected industries. We then estimate (10) and include the diagonal of the input-output matrix in the construction of the downstream and upstream exposure measures, to study the effects of protection on all industries. The results in column 2 of Table A-13 confirm that AD duties have a net negative impact on US jobs: they reduce the growth rate of employment in downstream industries, and have no significant effects in other industries.

Using the methodology proposed by Acemoglu *et al.* (2016), we can use the estimates of Table A-13 to quantify the number of jobs lost due to AD protection. To this purpose, we compute counterfactual job losses as

$$\Delta L^{cf} = \sum_{j,T} L_{j,T}(1 - e^{-\hat{\beta}\Delta\widetilde{\tau}}), \tag{11}$$

where $L_{j,T}$ is the employment level in industry j at the end of period T, $\hat{\beta}$ is the estimated coefficient of Δ*Downstream Tariff Exposure*$_{j,T}$ from column 2 of Table A-13, and $\widetilde{\tau}$ is the predicted increase in input protection, estimated by multiplying the observed increase in Δ*Downstream Tariff Exposure*$_{j,T}$ with the partial R^2 (0.079) from the first-stage regression of the specification reported in column 1 of Table A-13.

Applying this methodology, we find that around 2.1 million US jobs were lost across all industries during 1992-2016 due to AD protection against China. This figure corresponds to 6.6% of the 32.7 million jobs the US economy added during this period.[57] If we compute (11) with the estimates obtained using the alternative AD measures ($\textit{Alternative Duty}_{i,T}$ and $\textit{Product Coverage}_{i,T}$), we obtain around 1.4 million jobs lost, while including all TTBs (AD, countervailing duties, safeguards) raises the counterfactual job losses to 2.2 million. These estimates imply that, in the absence of trade protection, fewer jobs would have been destroyed (more jobs would have been created) in downstream declining (expanding) industries.

Table A-14 in the Appendix lists the ten downstream industries most negatively affected by input protection.[58] These include large non-manufacturing industries, which have faced high AD duties on some of their key inputs. For example, our estimates imply that during 1992-2016 almost 250,000 additional jobs would have been created in the construction industry (SIC 1510) in the absence of AD duties against China. These losses are mostly due to the protection of steel, the most important input for construction, with duties ranging from 55% (stainless pressure pipes) to 430% (drill pipes). Another example is the restaurant industry (SIC 5812). Our estimates imply that without AD protection against China around 210,000 additional jobs would have been created in the restaurant industry during 1992-2016. In this period, the restaurant industry faced high AD protection on some key inputs, with duties of up to 203% and 113% on crawfish and shrimps.[59]

The results reported so far show that AD duties reduce employment growth in downstream sectors, with no significant effects in protected and upstream sectors. Using data from the NBER-CES Manufacturing Industry Database, we can examine whether both production and non-production jobs are affected. The results reported in Table A-15 show that trade protection has detrimental effects on both types of jobs in downstream industries. While we find no positive effects on employment growth, there is some evidence that AD duties increase wages in protected industries. This can be seen by looking at columns 5-6 of Table A-15, in which we study the effects of protection on real wages, using data from

[57] Acemoglu *et al.* (2016) apply their counterfactual exercise to their baseline specification, which does not control for SIC4 sectoral trends. We thus de-trend industry employment when computing (11).

[58] The number of estimated job losses reported in this table is obtained by carrying out the counterfactual exercise in (11) by SIC4 industry.

[59] Debaere (2009) studies an AD case filed by the Southern Shrimp Alliance (SSA), which in 2004 led to duties being imposed on shrimp imports from several countries (China, Thailand, Vietnam, India, Brazil, and Ecuador). He notes that eight SSA states were expected to be "political battlegrounds" in the elections, which helps explain why the duties were introduced, notwithstanding strong opposition by US seafood distributors, retailers, restaurateurs, and other businesses involved in shrimp processing and marketing.

the NBER-CES dataset: AD duties increase wage growth in protected industries (the coefficient of $\Delta Direct\ Tariff\ Exposure_{j,T}$ is positive and significant), but have no effect on wages in downstream and upstream industries.

In Table A-15, we use the same instrument to study the effects of trade protection on different outcome variables (production and non-production jobs, wages). As explained by Heath *et al.* (2019), this may lead researchers to over-reject the null (an increase in the number of Type I errors), resulting in biased causal inferences. To account for this, we use the procedure developed by Romano and Wolf (2005, 2016) that controls for the family-wise error rate (probability of making at least one false rejection among the hypotheses) and the dependence across tests. By considering the three outcome variables jointly, and applying the Romano-Wolf correction with 1,000 bootstrapped replications, we find that the coefficients of downstream tariff exposure variables retain their statistical significance in the production and non-production worker regressions in columns 2 and 4. However, the Romano-Wolf p-values for the coefficients on wages in columns 5 and 6 jump to 0.21 and 0.25 respectively, indicating that the wage results are not robust to this correction.

In Appendix A-4, we provide evidence for the mechanisms behind the negative effects of protection on employment growth along supply chains: AD duties against China decrease US imports of targeted products and raise both domestic and import prices, increasing production costs for downstream industries.

6.2 Identification and Additional Robustness Checks

In this section, we perform a series of additional estimations to verify the robustness of our main results. First, we address omitted variable concerns. As discussed in Section 5.2, our identification strategy relies on a shift-share research design: exogenous changes in the identity of swing states across electoral terms, combined with heterogeneous exposure to these shocks across industries, depending on their importance across states (captured by initial employment shares), their historical experience in the AD process (captured by pre-sample AD petitions), and vertical linkages (captured by input-output shares). Non-random exposure to the shocks could give rise to an omitted variable bias (OVB) in the IV estimates. Borusyak and Hull (2021) explain how to purge OVB from non-random exposure to the shocks, without having to impose further assumptions (such as parallel trends). Their methodology requires measuring and appropriately adjusting for the "expected" instrument, constructed by drawing many counterfactual shocks from the assignment process. They show that "recentering" — by controlling for the expected instrument or subtracting it from the

IV — removes the bias from non-random shock exposure.

To apply the recentering methodology, we construct counterfactual shocks by randomly choosing the identity of swing states. We perform two types of randomization among the 32 states that were classified as swing at least once during the last eight presidential terms. In the first one, we keep the number of swing states in a given term as in Figure 2 (e.g. 6 states for the presidential term 2008-2012 and 4 states for 2012-2016). We perform 5,000 randomizations of swing states. Each randomization consists of independent random draws of swing states, one per presidential term. From each randomization, we obtain a variable $\textit{Placebo Swing State}_{1,s,T}$, which we use to construct $\textit{Placebo IV}_{1,j,T}$. We then average across the 5,000 draws to obtain $\textit{Expected IV}_{1,j,T}$. In the second type of randomization, we fix the number of times in which a state is swing to be the same as in Figure 2 (e.g. 5 for Ohio, 4 for Florida, 3 for Missouri). Again, we perform 5,000 randomizations, each generating a $\textit{Placebo Swing State}_{2,s,T}$, which we use to construct $\textit{Placebo IV}_{2,j,T}$. By averaging across randomizations, we obtain $\textit{Expected IV}_{2,j,T}$.

In Table 5, we include the expected instruments for changes in direct, downstream and upstream tariff exposure, constructed based on the first randomization (top panel) and the second randomization (bottom panel) in the specifications of Table 4.[60] Following Borusyak and Hull (2021) and Borusyak *et al.* (2021), we report in brackets 95% confidence intervals, obtained by a wild score bootstrap (with 1,000 replications). The coefficient of $\Delta \textit{Downstream Tariff Exposure}_{j,T}$ is always negative and significant, while the coefficients of the other tariff exposure variables are never significant. Table 5 shows that our results on the employment effects of protection are robust to addressing OVB concerns.

Our instrument is a (non-linear) shift-share instrumental variable (SSIV) with "incomplete" input-output shares: heterogeneous exposure to trade protection across downstream industries is captured by $\sum_{i=1}^{N} \omega_{i,j}$ in equation (2), which does not sum up to one since not all inputs used by industry j are tradable; the same is true for exposure across upstream industries, which is captured by $\sum_{i=1}^{N} \theta_{i,j}$ in equation (3). The inclusion of SIC4 fixed effects controls for heterogeneous reliance on tradable industries.[61] Notice that including SIC4 fixed effects and clustering standard errors at the SIC3 level also helps to address the concern that observations with similar exposure shares may have correlated residuals (Adão *et al.*, 2019). Our results are robust to clustering at the broader SIC2 level, in which shares become more

[60] The coefficients of these variables (omitted) are sometimes statistically significant, but their signs are not stable across randomizations.

[61] We verify that our results continue to hold when we add interactions of the sum of input-output shares with term fixed effects, as proposed by Borusyak *et al.* (2021) for linear SSIVs with incomplete shares. These results are available on request.

dissimilar, as shown in Table A-16.

Table 5

The impact of protection on employment along supply chains (recentering the IV)

	Recentering using *Expected* $IV_{1,j,T}$			
	Tradable sectors		All sectors	
	(1)	(2)	(3)	(4)
Δ*Direct Tariff Exposure*$_{j,T}$	-0.004	-0.590		
	(1.765)	(1.533)		
Δ*Downstream Tariff Exposure*$_{j,T}$		-15.714***	-20.939***	-19.340***
		(4.325)	(5.783)	(5.092)
		[-28.2, -6.715]	[-40.95, -9.991]	[-34.66 , -10.39]
Δ*Upstream Tariff Exposure*$_{j,T}$		-2.894	-6.539	-2.440
		(6.889)	(7.360)	(6.133)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,833	2,833	3,351	3,351
KP F-statistic	9.49	3.93	31.9	57.6
	Recentering using *Expected* $IV_{2,j,T}$			
	Tradable sectors		All sectors	
	(1)	(2)	(3)	(4)
Δ*Direct Tariff Exposure*$_{j,T}$	-0.512	-0.622		
	(1.257)	(1.325)		
Δ*Downstream Tariff Exposure*$_{j,T}$		-16.447***	-20.011***	-18.846***
		(5.293)	(5.780)	(5.258)
		[-33.92, -5.815]	[-41.45, -8.694]	[-36.71, -8.384]
Δ*Upstream Tariff Exposure*$_{j,T}$		1.928	-1.311	0.759
		(5.117)	(5.963)	(5.196)
Observations	2,833	2,833	3,351	3,351
KP F-statistic	27.5	7.26	63.5	104.6

The table reports 2SLS estimates. The dependent variable $\Delta L_{j,T}$ is the log change in employment in SIC4 industry j during term T. The tariff variables capture changes in the exposure to AD protection, as measured by (1)-(3), instrumented using changes in the corresponding IV variables. Δ*Downstream Tariff Exposure*$_{j,T}$ and Δ*Upstream Tariff Exposure*$_{j,T}$ are constructed incorporating higher-order input-output linkages. In columns 2-3 (column 4), we exclude (include) the diagonal of the input-output matrix in the construction of these variables. Each specification in the top (bottom) panel includes direct and indirect expected tariff exposure measures, constructed using *Expected* $IV_{1,j,T}$ (*Expected* $IV_{2,j,T}$). The coefficients of these variables and of the direct and indirect Δ*Swing Industry* variables included in (8)-(10) are not reported. The sample covers 1988-2016. In columns 1 and 2 (3 and 4), it comprises tradable sectors (all sectors). Observations are weighted by 1988 employment. Standard errors clustered at the SIC3 industry level reported in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively. 95% confidence intervals, obtained by a wild score bootstrap, reported in brackets.

Table 6

The impact of protection on employment along supply chains (controlling for subsidies)

	Tradable sectors		All sectors	
	(1)	(2)	(3)	(4)
Δ*Direct Tariff Exposure*$_{j,T}$	-0.608	-0.474		
	(0.733)	(0.589)		
Δ*Downstream Tariff Exposure*$_{j,T}$		-12.655***	-19.509***	-18.043***
		(4.300)	(5.052)	(4.490)
Δ*Upstream Tariff Exposure*$_{j,T}$		0.208	-2.287	-1.008
		(2.129)	(3.488)	(3.104)
Δ*Direct Subsidy Exposure*$_{j,T}$	0.002***	0.003***		
	(0.001)	(0.001)		
Δ*Downstream Subsidy Exposure*$_{j,T}$		0.026***	0.027***	0.026***
		(0.007)	(0.006)	(0.006)
Δ*Upstream Subsidy Exposure*$_{j,T}$		0.013**	0.016**	0.016**
		(0.006)	(0.007)	(0.007)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,618	1,618	1,914	1,914
KP F-statistic	70.9	17.8	61.0	93.8

The table reports 2SLS estimates. The dependent variable $\Delta L_{j,T}$ is the log change in employment in SIC4 industry j during term T. The tariff variables capture changes in the exposure to AD protection, as measured by (1)-(3), instrumented using changes in the corresponding IV variables. The variable Δ*Direct Subsidy Exposure*$_{j,T}$ is the log change in federal and state-level subsidies received by industry j during term T, while Δ*Downstream Subsidy Exposure*$_{j,T}$, and Δ*Upstream Subsidy Exposure*$_{j,T}$ measure subsidies granted to vertically related industries. The downstream and upstream tariff and subsidy variables are constructed incorporating higher-order input-output linkages. In columns 2-3 (column 4), we exclude (include) the diagonal of the input-output matrix in the construction of these variables. The coefficients of the direct and indirect Δ*Swing Industry* variables included in (8)-(10) are not reported. The sample covers 2000-2016. In columns 1 and 2 (3 and 4), it comprises tradable sectors (all sectors). Observations are weighted by 1988 employment. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Second, we address concerns about the exclusion restriction. To obtain a consistent estimate of the causal impact of AD protection, our proposed instrumental variable should be uncorrelated with other determinants of the dependent variable. One may be concerned that our instrument could pick up the effects of other policies – in particular federal and state-level subsidies – that could be used to support industries that are important in swing states. We have already addressed this issue in two ways. First, as discussed in Section 5.2, our instrument is AD specific, since it is defined as the interaction between *Swing Industry*$_{j,T}$ and *AD Experience*$_i$, implying that we only exploit variation in the political importance of an industry to the extent that this is relevant for AD protection. Second, in all 2SLS regressions we control for changes in $Swing\ Industry_{j,T}$ — and the corresponding changes along supply chains — to account for the effects of other policies that may be used to favor important industries in swing states. As a final check, we explicitly control for federal and state-level subsidies, using information from Subsidy Tracker. As discussed in Section 4.3, this dataset provides information on subsidies by recipient firms from state, local, and federal economic programs, which we use to construct subsidy measures at the industry-year level.

Table 6 reproduces Table 4, now including changes in industry-level subsidies. Notice that the number of observations is smaller than in Table 4, since data on subsidies is only available from 2000. The subsidy variables are constructed like the corresponding tariff variables and include all subsidies (the results are similar if we include only federal or state-level subsidies). The results confirm our key finding: AD protection causes net job losses along supply chains, since it decreases the growth rate of employment in downstream industries and has no significant effect on the growth rate of employment in protected and upstream industries. Although we do not instrument for the subsidy exposure measures, the positive and significant coefficients of these variables suggest that subsidies may generate job gains along supply chains.

We have performed a series of additional estimations to verify the robustness of our results. Our baseline 2SLS regressions in differences include sector fixed effects defined at the SIC4 level. This allows us to account for time-invariant industry characteristics and sectoral trends. In Table A-17, we reproduce Table 4 using broader or no industry fixed effects. The results confirm that trade protection against China has a negative effect on employment growth in downstream industries.

In Table A-18, we extend our analysis to protectionist measures introduced during the first two years of Trump's presidency.[62] Since 2017, China has been the target of even higher AD protection (see Figure 1). Moreover, in 2018 Trump introduced additional tariffs, which were stacked on top of existing AD duties. In column 1, we reproduce the benchmark specification (column 4 of Table 4), including AD duties introduced during 2017-2018; in column 2, we further include all TTBs (AD duties, countervailing duties, safeguards) applied against China since 1988, as well as the additional tariffs introduced during Trump's presidency; in column 3, we also account for retaliatory tariffs. In all specifications, the coefficient of $\Delta Downstream\ Tariff\ Exposure_{j,T}$ remains negative and significant.[63]

[62] We are not able to cover the entire term due to lack of employment data.

[63] Notice that the instrument is much weaker when including Trump's special tariffs on top of AD duties (columns 2-3). As discussed in Section 4, these tariffs exhibit little variation across SIC4 industries, both on

In Table A-19 we reproduce Table 4, controlling for MFN tariffs.[64] In these regressions, we also include Chinese duties on US goods, since several studies (e.g. Blonigen and Bown, 2003; Feinberg and Reynolds, 2006) emphasize retaliatory motives in AD filings. Our results on the negative effects of AD duties are unaffected (and there is some evidence of negative effects of retaliation).

6.3 Trade Protection and the China Shock

Our paper is related to a series of influential studies that have examined the labor market effects of rising import competition from China.[65] Following Autor *et al.* (2013), most of these studies use Chinese import growth in other high-income markets ($\Delta IPO_{j,t}$) as an instrumental variable for the growth in US imports from China, to isolate the foreign-supply-driven component of changes in US import penetration.

These studies have not accounted for the rise in US trade protection against China during the last few decades, as illustrated by Figures 1 and A-1. If US trade protection is correlated both with the instrument used in the China shock literature and employment growth, omitting this variable could bias the estimated effect of Chinese import competition on employment growth.[66] On the other hand, the fact that the China shock has increased political polarization in US counties (Autor *et al.*, 2020a) may have caused certain states to be classified as swing (though in Appendix A-2 we find no evidence for this). For these reasons, it is crucial to examine the relationship between the two instruments and how they jointly affect US employment.

We first examine the relationship between $\Delta IV_{j,t}$ and $\Delta IPO_{j,t}$ and find that their correlation is very low (-0.007) and insignificant. We also find that $\Delta IV_{j,t}$ is uncorrelated with actual changes in Chinese import competition, and $\Delta IPO_{j,t}$ is uncorrelated with actual changes in US protection. This surprising finding is partly due to the fact that the most import-competing sectors (e.g. apparel, toys, computers) did not receive high AD protection in our sample period, possibly because they had little or no experience in AD proceedings. This suggests that the two instruments can be used separately to identify the effects of

the extensive and intensive margin, which makes it harder to apply our IV strategy.

[64] Our results do not change if instead of MFN tariffs, we use effectively applied tariffs that take into account US preferential tariffs.

[65] See Autor *et al.* (2016) for an extensive literature review on the China shock.

[66] If the United States was able to use AD duties to curb imports and shelter employment in the most import-competing industries, the estimates would have a positive bias, reducing the size of the negative effects of import competition on employment. Moreover, as shown by Bown and Crowley (2007), AD measures can deflect exports of the targeted country to third countries, suggesting that some of the variation in the instrument used in the China shock literature might be explained by US AD duties.

Chinese import competition and trade protection against China along supply chains.

Second, we jointly examine the two channels. We include our tariff exposure measures in the econometric model of Acemoglu *et al.* (2016), with stacked first differences for the time periods 1991-1999 and 1999-2011. To be consistent with their analysis, we include broad industry fixed effects. The results of these estimations are reported in Table A-20.

In columns 1-3, we include the direct tariff and import exposure measures, first separately, then together. A few remarks are in order. First, the coefficients of $\Delta \mathit{Direct\ Tariff\ Exposure}_{j,t}$ and $\Delta \mathit{Direct\ Import\ Exposure}_{j,t}$ are very similar if estimated in isolation or jointly. This is not surprising given that the two instruments are uncorrelated. Second, the results confirm our finding that AD duties against China has no significant effect on employment in protected industries and Acemoglu *et al.* (2016)'s finding that rising import competition from China has a negative impact on employment growth in directly exposed industries. Finally, notice that in these regressions the sample is restricted to manufacturing industries, since $\Delta IPO_{j,t}$ can only be constructed for these industries.

To study the effects on all industries, in column 4, we regress employment growth on the measures of downstream and upstream exposure to protection and import competition, constructed including the diagonal of the input-output matrix. The estimates confirm our finding that AD duties against China have a negative impact on employment in downstream industries and Acemoglu *et al.* (2016)'s finding that import competition from China reduces employment growth in upstream industries. We use these estimates and apply the methodology of Acemoglu *et al.* (2016) to compute the counterfactual number of jobs lost due to Chinese import competition and AD protection against China. We find that around 2.3 million jobs were lost in the US economy due to rising import competition from China during 1991-2011, and 960,000 jobs were lost in the same period due to AD protection against China. Overall, the results of Table A-20 indicate that rising import competition from China has detrimental effects on US employment, and trade protection against China generates additional job losses.

7 Conclusion

The US-China trade war triggered by President Trump's 2018 tariffs has stimulated a flourishing literature on the costs of protection. In this paper, we show that, well before President Trump took office, the US had been using protectionist measures against China, in the form of AD duties. Combining 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 instrument for AD duties by exploiting exogenous variation in the political importance of different industries and their historical experience in dealing with the complex AD proceedings. We find that AD protection decreases employment growth in downstream industries (affecting both production and non-production jobs), and has no significant effects on employment in protected and upstream industries. We further provide evidence for the mechanisms behind the negative effects of protection along supply chains: AD duties decrease imports and raise prices in protected industries, increasing production costs in downstream industries.

Our identification strategy is based on a shift-share research design, which studies the impact of a set of shocks on units that are differentially exposed to them. We address concerns about potential omitted variable bias due to non-random exposure to the shocks, as well as concerns related to the exclusion restriction. Our results continue to hold when controlling for rising import competition from China and in a battery of robustness checks.

In terms of magnitude, our baseline estimates imply that a one standard deviation increase in the average input tariff faced by an industry decreases the growth rate of employment in that industry by 5.3 percentage points, which explains 24.6% of the standard deviation of employment growth. When we apply the methodology of by Acemoglu *et al.* (2016) to compute counterfactual job losses, our estimates imply that around 2.1 million US jobs were lost across all industries during 1992-2016 due to AD protection against China, which corresponds to 6.6% of the 32.7 million jobs the US economy added during this period.

Our findings resonate with concerns often heard in the media about the costs of protection along supply chains.[67] As mentioned in the introduction, vocal arguments about the cost of protection against China have recently been raised by US business associations in a letter to the Biden administration.

Note that our analysis does not capture the full general equilibrium impact of protection against China, which encompasses other indirect channels through which trade barriers may affect employment. These include reallocation effects: if some industries contract in a local labor market as a result of trade protection against China, some other industries in the same market might expand. An additional channel operates through aggregate demand effects: the net job losses that we identify along supply chains can generate additional job losses in

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

sectors not otherwise exposed to protection, through a fall in demand for goods and services, as suggested by the literature on local multipliers (e.g. Moretti, 2010; Mian and Sufi, 2014). An important avenue of future research is to estimate the reallocation and aggregate demand effects of trade protection at the level of local labor markets.

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 Chinese import competition as the cause for the decline in manufacturing jobs and have extensively used AD duties to protect their economies against China. We find that, rather than fostering employment growth, politically-motivated protectionist measures give rise to additional job losses.

Finally, this paper also contributes to the academic debate about the rationale for allowing flexible protectionist measures such as AD in trade agreements. Previous studies provide an economic rationale: the ability to protect industries in the face of import surges can act as a "safety valve," allowing countries to sustain trade policy cooperation (Bagwell and Staiger, 1990). Our paper emphasizes political economy motives for flexible trade barriers (in the spirit of Bagwell and Staiger, 2005): being able to protect certain industries can help politicians to gain votes. These motives are particularly important in the United States, where swing-state politics creates incentives to favor key industries in battleground states.

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Appendices (for Online Publication Only)

A-1 Concordance of HS to SIC4

As explained in Section 4.2, the Temporary Trade Barriers Database (TTBD) contains detailed information on AD duties and other protectionist measures (countervailing duties and safeguards). For US AD cases, it provides detailed information on the products under investigation, with petitions identified at the 10-digit Harmonized Tariff Schedule (HTS) level (or at the 5-digit Tariff Schedule of the United States Annotated for years before 1989).

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

We then match the HS codes to the SIC classification using the following procedure:[68]

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.[69] In order to map each HS6 product to only one industry, we assign an HS6 code to the industry which accounts for the largest share of that product's US imports. This means that each HS6 product is mapped to only one 4-digit SIC industry. AD cases often target multiple HS6 products and thus may be linked to more than one SIC4 code.

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

[68]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.

[69]For the years up to 1988, descriptions of products were provided according to the Tariff Schedule of the United States Annotated (TSUSA) classification. Therefore, for AD cases before 1988, we match each TSUSA code with a corresponding HS code using the correspondence table provided by Feenstra (1996), available at http://cid.econ.ucdavis.edu/usix.html.

A-2 Exogeneity of the Identity of Swing States

Our identification strategy relies on the assumption that the political shocks are exogenous: AD protection does not affect the identity of swing states in presidential elections, i.e. in which states the difference in vote shares between the Democratic and Republican candidates is below the 5% threshold.

To support the validity of this assumption, we examine whether changes in AD protection are correlated with changes in the identity of swing states. We construct a measure of exposure to AD protection at the state-term level, $Duty_{s,T} = \sum_j \alpha_{s,j} Duty_{j,T}$, where $Duty_{j,T}$ is the average AD duty applied to imports from China across all HS6 products in industry j in the last year of term T and $\alpha_{s,j}$ is the 1988 share of employment in industry j in total employment of state s.

Since our 2SLS regressions are estimated in term differences, we verify that changes in AD duties are not associated with changes in the identity of swing states, by estimating:[70]

$$\Delta Swing\ State_{s,T} = \beta_0 + \beta_1 \Delta Duty_{s,T} + \delta_s + \delta_T + \varepsilon_{s,T}, \tag{12}$$

where $\Delta Swing\ State_{s,T}$ captures changes in the identity of swing states (between the election in year $T-1$ and the election in year T) and $\Delta Duty_{s,T}$ measures the corresponding changes state-level AD protection. As shown in column 1 of Table A-1, the β_1 coefficient is not significant, indicating that changes in the identity of swing states are not correlated with changes in AD protection.

One may be concerned that the identity of swing states could be correlated with the degree of import competition. If so, this would be a violation of the exclusion restriction since import competition can also affect labor market outcomes. To address this concern, we substitute $\Delta Duty_{s,T}$ in equation (12) with $\Delta Import\ Exposure_{s,T}$ or $\Delta Import\ Exposure\ China_{s,T}$, which capture state-level changes in import competition (from all countries or China only).[71] As shown in columns 2 and 3 of Table A-1, the coefficients of these variables are not significant, indicating that changes in import competition are not associated with changes in the identity of swing states.

[70] The results are similar if we replace $\Delta Swing\ State_{s,T}$ by $Swing\ State_{s,T}$.

[71] We first construct industry-level measures of import penetration, $Import\ Exposure_{j,T}$ and $Import\ Exposure\ China_{j,T}$, using information on trade flows and production. The state-level variables are defined as $Import\ Exposure_{s,T} = \sum_j \alpha_{s,j} Import\ Exposure_{j,T}$ and $Import\ Exposure\ China_{s,T} = \sum_j \alpha_{s,j} Import\ Exposure\ China_{j,T}$, where $\alpha_{s,j}$ is the 1988 share of employment in industry j in total employment of state s.

Table A-1

AD protection, import competition, and the identity of swing states

	(1)	(2)	(3)
$\Delta Duty_{s,T}$	0.20		
	(0.42)		
$\Delta Import\ Exposure_{s,T}$		-0.03	
		(0.03)	
$\Delta Import\ Exposure\ China_{s,T}$			-0.14
			(0.09)
State FE	Yes	Yes	Yes
Term FE	Yes	Yes	Yes
Observations	336	336	336
Adjusted R^2	0.07	0.07	0.07

The table reports OLS estimates of equation (12). The dependent variable is $\Delta Swing\ State_{s,T}$, which captures changes in the identity of swing states (between the election in year $T-1$ and the election in year T). The sample covers 1988-2016. Standard errors in parentheses are clustered at the state level. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

A-3 Micro-level Evidence on AD Protection

In this section, we provide micro-level evidence supporting our instrument for AD protection. First, we show that legislators from swing states are overrepresented in the key committees dealing with trade policy in the US Congress. We then show that our instrument is a strong predictor of AD votes of ITC commissioners and the outcome of AD petitions.

As mentioned before, previous studies on the political economy of US AD policy shows that votes by ITC commissioners reflect the interests of the members of the Finance committee in the Senate and the Ways and Means committee in the House, the two powerful committees dealing with trade policy in Congress (e.g. Moore, 1992; Hansen and Prusa, 1997; Aquilante, 2018). These studies suggest that the composition of these committees should affect AD votes by ITC commissioners. Using data on committee membership,[72] we find that legislators from swing states are overrepresented in these committees: during the eight presidential elections in 1988-2016, swing states accounted for around 21% of US states on average (see Figure 2). However, around 33% (36%) of the new members of the

[72] These data are available from Charles Stewart III and Jonathan Woon, Congressional Committee Assignments, 103rd to 114th Congresses, 1993-2017.

Senate Finance (House Ways and Means) committee in a presidential term represented states classified as swing.

This composition bias in the key trade committees may lead ITC decisions to be skewed in favor of key industries in swing states, particularly if they have previous AD experience. To verify this, we use the dataset on ITC votes by Aquilante (2018), which covers the 1985-2008 period, and update it till 2020. The ITC is composed of six commissioners who are appointed for nine non-renewable years.[73] We collect commissioners' final votes on material injury, focusing on AD cases involving China as a target country.[74] During each year of his or her tenure, each commissioner casts many votes involving different industries.[75]

We estimate the following:

$$Vote_{j,t,c} = \beta_0 + \beta_1 IV_{j,T} + \delta_j + \delta_t + \delta_c + \varepsilon_{j,t,c}. \tag{13}$$

The dependent variable is $Vote_{j,t,c}$, a dummy variable which is equal to 1 if ITC commissioner c votes in favor of AD duties against China in year t, in a case involving SIC4 industry j.[76] The variable $IV_{j,T}$ defined in equation (4) measures the importance of industry j in states classified as swing during term T, interacted with its historical experience in AD proceedings. We include industry, year, and commissioner fixed effects (denoted by δ_j, δ_t and δ_c). We first estimate (13) on ITC votes cast between 1985 (the first year of Aquilante's dataset) and 2016 (the end of our main sample period). We then extend the analysis to all votes in the 1985-2020 period. The results are reported in columns 1 and 4 of Table A-2, respectively. The coefficient of $IV_{j,T}$ is positive and significant at the 1% level, confirming that ITC commissioners are more likely to vote in favor of AD when the petitioning industry is more important in swing states and has AD experience.

[73] In reality, the tenure of ITC commissioners is often shorter and (in a few cases) longer than 9 years (see Aquilante, 2018).

[74] Similar results are obtained looking at AD cases involving all countries.

[75] Focusing on AD cases against China, during 1985-2020, ITC commissioners have cast on average 64 votes (10 per year).

[76] We exclude abstentions (3% of observations) from our sample.

Table A-2

Predicting ITC votes and the outcome of AD petitions

	1985-2016			1985-2020		
	Votes	Vote shares	Outcome	Votes	Vote shares	Outcome
	(1)	(2)	(3)	(4)	(5)	(6)
$IV_{j,T}$	0.492***	0.423***	1.383***	0.386***	0.372***	1.027***
	(0.075)	(0.074)	(0.198)	(0.066)	(0.065)	(0.188)
Commissioner FE	Yes	No	No	Yes	No	No
SIC4 FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.51	0.29	0.30	0.52	0.33	0.30
Observations	1,526	214	255	1,864	273	306

The table reports OLS estimates. In columns 1 and 4, the dependent variable is $Vote_{j,t,c}$, a dummy variable which is equal to 1 if ITC commissioner c votes in favor of AD duties against China in year t, in a case involving SIC4 industry j. In columns 2 and 5, the dependent variable is $Vote\ Share_{j,t}$, the share of ITC commissioners voting in favor of AD duties against China in year t, in a case involving industry j. In columns 3 and 6, the dependent variable is the $Outcome\ of\ AD\ Petition_{j,t}$, a dummy variable equal to 1 if an AD measure is introduced in year t following a petition by industry j. $IV_{j,T}$ is defined in equation (4). In columns 1-3 (4-6), the sample covers 1985-2016 (1985-2020). Standard errors in parentheses are clustered at the SIC3 industry level. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Previous studies emphasize the importance of peer effects in legislative voting (e.g. Harmon *et al.*, 2019), suggesting that ITC commissioners may be affected by their colleagues when voting on AD. To allow for these interdependences, we examine the role of swing-state politics at a more aggregate level, estimating the effects of $Swing\ Industry_{j,T}$ on the share of politicians that vote in favor of AD:

$$Vote\ Share_{j,t} = \beta_0 + \beta_1 IV_{j,T} + \delta_j + \delta_t + \varepsilon_{j,t}. \tag{14}$$

The results of this estimation are reported in columns 2 and 5 of Table A-2. The coefficient of $IV_{j,T}$ remains positive and significant. Finally, we examine whether our instrument can help to explain the outcome of AD petitions:

$$Outcome\ of\ AD\ Petition_{j,t} = \beta_0 + \beta_1 IV_{j,T} + \delta_j + \delta_t + \varepsilon_{j,t}. \tag{15}$$

The dependent variable is a dummy variable equal to 1 if an AD measure is introduced in year t following a petition by industry j. Recall that a measure is introduced if both the

DOC and ITC rule in favor of the petitioning industry (see Section 3 for details). The results reported in columns 3 and 6 of Table A-2 show that our instrument increases the probability of a successful AD petition.[77]

A-4 Mechanisms

The results reported in Section 6 show that AD duties have negative effects along supply chains, reducing the growth rate of employment in downstream industries, with other significant effects in other industries. In what follows, we provide evidence for the mechanisms behind these results: higher tariffs decrease imports and raise (domestic and import) prices in targeted industries, raising production costs for downstream industries.

We consider first the effects on AD duties on US imports of targeted products from China by estimating the following 2SLS regression:[78]

$$\Delta \textit{Imports from China}_{j,t} = \beta_0 + \beta_1 \Delta \textit{Direct Tariff Exposure}_{j,t} + \beta_2 \Delta \textit{Swing Industry}_{j,T} + \delta_j + \delta_t + \varepsilon_{j,t}. \tag{16}$$

The dependent variable is the 4-year change in log imports in sector j from China in year t. The key explanatory variable of interest is $\Delta \textit{Direct Tariff Exposure}_{j,t}$, the 4-year change in AD duties against China.[79] $\Delta \textit{Swing Industry}_{j,T}$ captures changes in the political importance of industry j during term T, while δ_j and δ_t denote industry (SIC4) and year fixed effects, respectively. The results of estimating (16) are reported in column 1 of Table A-3. The β_1 coefficient is negative and significant at the 1% level, confirming that AD duties against China are effective in reducing Chinese imports.

[77] In unreported results, we use the discrete choice conditional logit model and find qualitatively similar results (available on request).

[78] This regression is based on tradable goods only. For the first presidential term in our sample period (1988-1992 term), we use data for 1991-1992 due to unavailability of import data prior to 1991.

[79] We run this regression at the year level to exploit the high variation of import growth across years. If we estimate the regression at the term level, we continue to find a similarly large negative effect of duties on imports from China, albeit with a p-value of 0.27.

Table A-3

The impact of AD duties on imports

	China	Top 50 exporters
	(1)	(2)
Δ*Direct Tariff Exposure*$_{j,t}$	-12.505***	0.547
	(2.322)	(3.136)
Δ*Direct Tariff Exposure*$_{j,t} \times$ *China*$_c$		-13.052***
		(3.913)
SIC4 FE	Yes	No
Year FE	Yes	No
SIC4 $\times$ Country FE	No	Yes
Year $\times$ Country FE	No	Yes
Observations	9,611	372,677
KP F-statistic	41.6	20.8

The table reports 2SLS estimates of equations (16) and (17). In column 1, the dependent variable is $\Delta Imports\ from\ China_{j,T}$, the 4-year change in log US imports from China in SIC4 industry j in year t, while in column 2 it is $\Delta Imports_{j,c,T}$, the 4-year change in log US imports in SIC4 industry j from country c in year t. $\Delta Direct\ Tariff\ Exposure_{j,t}$ is the 4-year change in the AD duty against China. $China_c$ is a dummy variable equal to 1 if the origin country is China. The coefficients of the control variables $\Delta Swing\ Industry_{j,T}$ and $\Delta Duty_{j,t,c}$ included in equations (16) and (17) are not reported. The sample covers all tradable industries in 1991-2016. Observations are weighted by 1988 employment. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

As mentioned in Section 2, a large literature has examined the effects of AD duties on trade flows. Several studies have shown that AD duties reduce imports from targeted countries, but may increase imports from non-targeted countries (e.g. Prusa, 1997; Konings *et al.*, 2001). We next examine whether AD protection against China led to an increase in imports from non-targeted countries (trade diversion). To this purpose, we estimate

$$\begin{aligned} \Delta Imports_{j,c,t} &= \beta_0 + \beta_1 \Delta Direct\ Tariff\ Exposure_{j,T} + \beta_2 \Delta Direct\ Tariff\ Exposure_{j,T} \times China_c \\ &\quad + \beta_3 \Delta Duty_{j,c,t} + \beta_4 \Delta Swing\ Industry_{j,t} + \delta_{j,c} + \delta_{c,t} + \varepsilon_{j,c,t}, \end{aligned} \tag{17}$$

where $\Delta Imports_{j,c,t}$ is the 4-year change in log imports of sector j from country c in year t and $China_c$ is a dummy variable equal to 1 if the origin country is China. The variable $\Delta Duty_{j,c,t}$ measures changes in AD protection against other countries. We include sector-country ($\delta_{j,c}$) and country-year ($\delta_{c,t}$) fixed effects to control for variables such as countries' comparative advantage and exchange rate fluctuations. The sample includes the top-50 largest exporters to the United States, ranked by their exports at the end of our sample period. The results reported in column 2 of Table A-3 show that AD duties against China significantly reduce imports from China: the trade destruction effect of AD is captured by the sum of the coefficients β_1 and β_2, which is negative and significant at the 1% level. We find no evidence that AD protection against China increased US imports from other countries: the estimated β_1 coefficient is insignificant.

We next consider the impact of AD duties on prices in protected industries. As mentioned before, a vast literature has studied the effects of tariffs on prices. For example, Amiti *et al.* (2019) show that Trump's tariffs had little-to-no impact on the prices received by foreign exporters, indicating that their incidence has fallen entirely on domestic consumers and importers. Using detailed producer price index (PPI) data, they also show that the 2018 tariffs increased the prices charged by US producers. Two channels are behind this increase in domestic prices: first, higher tariffs on the inputs used by an industry lead to higher prices in that industry, suggesting that producers pass on the increased cost of importing inputs to consumers; second, domestic producers raise their prices when competing import prices rise due to higher tariffs.

First, we use PPI data to examine the effects of AD duties on domestic prices:

$$\Delta \textit{Domestic Price}_{j,T} = \beta_0 + \beta_1 \, \Delta \textit{Direct Tariff Exposure}_{j,T} + \beta_2 \, \Delta \textit{Swing Industry}_{j,T} + \delta_j + \delta_T + \varepsilon_{j,T}, \tag{18}$$

where $\Delta \textit{Domestic Price}_{j,T}$ is the log change in the domestic price of goods in SIC4 industry j during term T. In these regressions, the sample includes only tradable industries, to which AD protection can apply. The results of estimating (18) are reported in column 1 of Table A-4. Notice that the number of observations is smaller than in the corresponding specification in Table 4 due to missing PPI data. The β_1 coefficient is positive and significant at the 1% level, confirming that AD protection raises domestic prices.[80]

We next examine the effects of AD protection on import prices.[81] The results are reported in column 2 of Table A-4. Again, the sample in this regression includes only tradable industries. The number of observations is smaller than in column 1 of Table 4 , due to missing data on unit values in the construction of $\Delta \textit{Import Price}_{j,T}$. The positive and significant coefficient of $\Delta \textit{Direct Tariff Exposure}_{j,T}$ indicates that AD duties raise the price of imported products.

[80] Consistent with this reasoning, De Loecker *et al.* (2014) find substantial declines in domestic prices due to trade liberalization in India.

[81] Blonigen and Haynes (2002, 2010) find pass-through rates of around 60% for US AD duties, but argue that these rates can theoretically exceed 100% due to special features of the US AD system such as "zeroing."

Finally, we consider the effects of AD duties on production costs. To this purpose, we first construct $\Delta Input\ Price_{j,T}$ by weighting domestic prices with cost shares, and regress it on $\Delta Downstream\ Tariff\ Exposure_{j,T}$. The results reported in column 3 of Table A-4 show that increasing AD duties increase input prices faced by downstream industries.

Table A-4

The impact of AD duties on prices

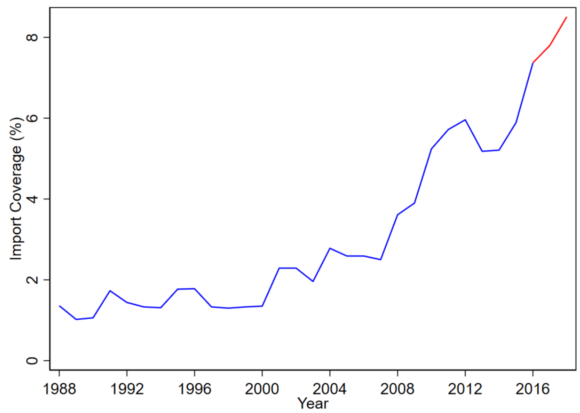
	Domestic prices	Import prices	Input prices
	(1)	(2)	(3)
$\Delta Direct\ Tariff\ Exposure_{j,T}$	3.796***	6.298**	
	(0.688)	(2.612)	
$\Delta Downstream\ Tariff\ Exposure_{j,T}$			5.702***
			(1.833)
SIC4 FE	Yes	Yes	Yes
Term FE	Yes	Yes	Yes
Observations	2,054	2,075	3,353
KP F-statistic	30.1	32.7	275.5

The table reports 2SLS estimates. In column 1 (column 2), the dependent variable is $\Delta Domestic\ Price_{j,T}$ ($\Delta Import\ Price_{j,T}$) the log change in the price of domestic (imported) goods in SIC4 industry j during term T. In column 3, the dependent variable is $\Delta Input\ Price_{j,T}$, the log change in the price of inputs faced by industry j during term T. The tariff exposure variables capture changes in the exposure to AD protection, as measured by (1)-(2), instrumented using changes in the corresponding IV variables. The downstream exposure variable is constructed incorporating higher-order input-output linkages and includes the diagonal of the input-output matrix. The sample covers 1988-2016; in columns 1 and 2 (column 3), it includes all tradable industries (all industries). Observations are weighted by 1988 employment. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

A-5 Figures and Tables

Figure A-1

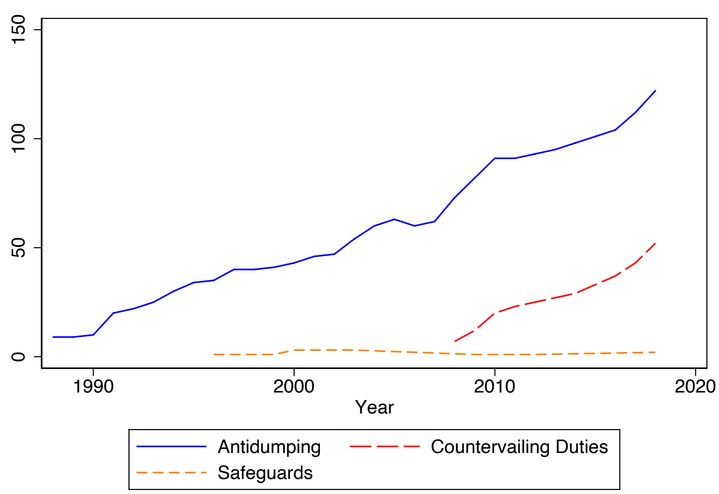
Share of US imports from China covered by AD duties



The figure plots the share of US imports from China at the 10-digit Harmonized Tariff Schedule level covered by US antidumping duties in 1988-2016 (in blue) and during Trump's presidency in 2017-2018 (in red). Source: Bown (2021).

Figure A-2

Number of US AD duties, countervailing duties, and safeguards against China (1988-2018)

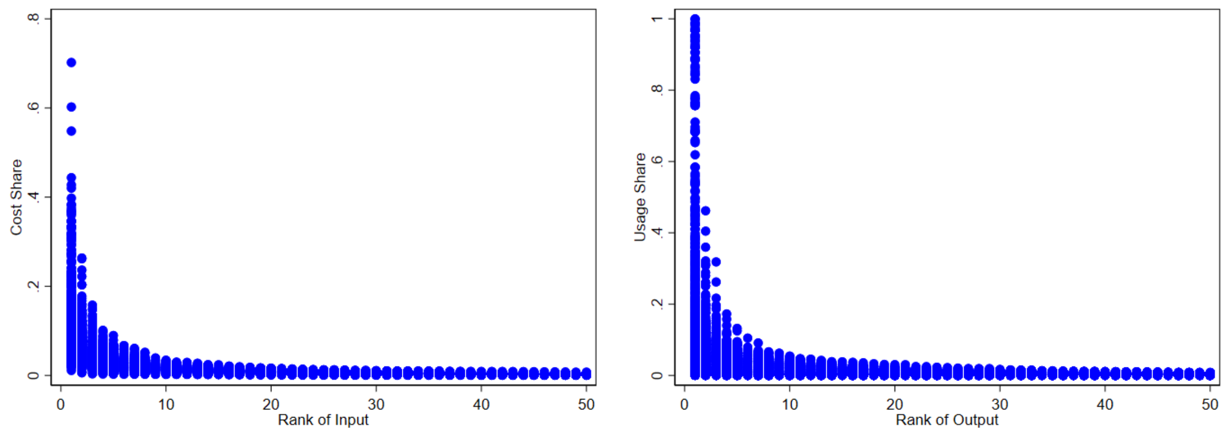


The figure plots the number of AD duties, countervailing duties, and safeguards applied by the US on imports from China. Source: Authors' calculations based on an extended version of the Temporary Trade Barriers Database.

Figure A-3

Distribution of IO coefficients

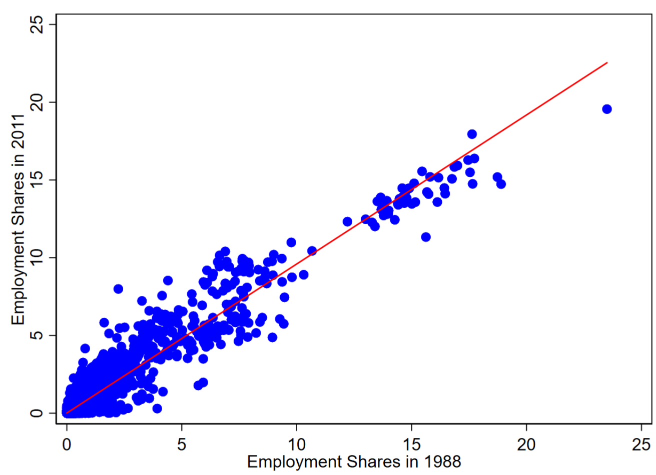
(a) Top-50 input industries (b) Top-50 output industries



The figures plot total cost and usage shares for the 479 SIC4 j industries, focusing on the top-50 input and output industries.

Figure A-4

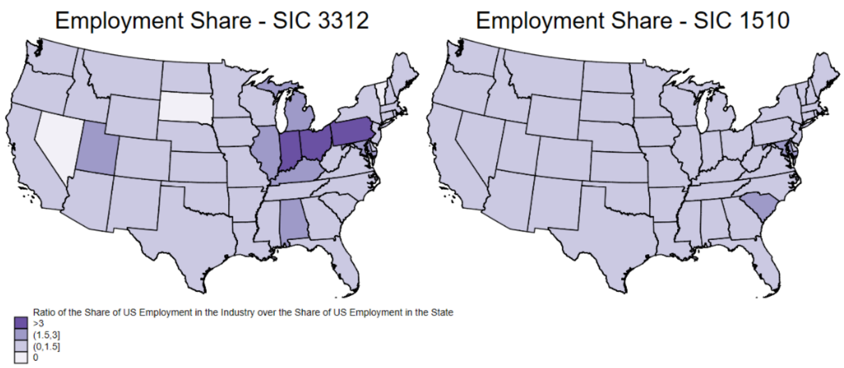
SIC4 employment shares by state



The figure plots state-level industry employment shares in 1988 and 2011, based on data from Acemoglu *et al.* (2016).

Figure A-5

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).

Table A-5

Top 10 input industries

SIC4	Input industry	Number of output industries	Average cost share
		(1)	(2)
3312	Blast furnaces and steel mills	82	10.8%
1221	Coal and petroleum	48	9.2%
2221	Broadwoven fabric mills, manmade	30	10.1%
2752	Commercial printing, lithographic	28	3.6%
2621	Paper mills	24	20.1%
3679	Electronic components, n.e.c.	23	6.0%
2869	Industrial organic chemicals, n.e.c.	20	10.9%
2821	Plastics materials and resins	12	12.0%
2911	Petroleum refining	12	10.0%
3674	Semiconductors and related devices	12	4.3%

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-6

Descriptive statistics of AD duties applied by the United States against China (1988-2016)

	Measures based on $Duty_{j,t}$			
Variable	Mean	Std. Dev.	Min	Max
$Direct\ Tariff\ Exposure_{j,t}$	2.1%	11.2%	0.0%	164.8%
$Downstream\ Tariff\ Exposure_{j,t}$	1.7%	2.2%	0.0%	29.2%
$Upstream\ Tariff\ Exposure_{j,t}$	1.1%	2.8%	0.0%	51.2%
	Measures based on $Alternative\ Duty_{j,t}$			
Variable	Mean	Std. Dev.	Min	Max
$Direct\ Tariff\ Exposure_{j,t}$	15.3%	53.9%	0.0%	430.0%
$Downstream\ Tariff\ Exposure_{j,t}$	12.9%	14.6%	0.1%	115.1%
$Upstream\ Tariff\ Exposure_{j,t}$	10.2%	21.1%	0.0%	236.0%
	Measures based on $Product\ Coverage_{j,t}$			
Variable	Mean	Std. Dev.	Min	Max
$Direct\ Tariff\ Exposure_{j,t}$	1.7%	7.5%	0.0%	100.0%
$Downstream\ Tariff\ Exposure_{j,t}$	1.5%	1.6%	0.0%	18.4%
$Upstream\ Tariff\ Exposure_{j,t}$	0.9%	2.0%	0.0%	33.2%

The table reports descriptive statistics of the tariff exposure variables defined in equations (1)-(3). The rates reported are ad valorem. The variable $Direct\ Tariff\ Exposure_{j,t}$ is constructed for the 405 tradable industries. The variables $Downstream\ Tariff\ Exposure_{j,t}$ and $Upstream\ Tariff\ Exposure_{j,t}$ are constructed for all 479 industries. They incorporate higher-order input-output linkages and include the diagonal of the input-output matrix.

Table A-7

Descriptive statistics of $IV_{j,T}$, $Swing\ Industry_{j,T}$ and $AD\ Experience_j$

Variable	Mean	Std. Dev.	Min	Max
$IV_{j,T}$	0.006	0.047	0	1.260
$Swing\ Industry_{j,T}$	0.002	0.004	0	0.045
$AD\ Experience_j$	1.126	2.874	0	48

The table reports descriptive statistics of our instrument for AD protection, $IV_{j,T}$, and of its components, $Swing\ Industry_{j,T}$ and $AD\ Experience_j$.

Table A-8

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

Swing Industry$_{j,T}$					
Sector	Description	Swing	Duty	Alternative Duty	Product Coverage
2752	Commercial printing, lithographic	0.030	2.4%	35.8%	2.1%
3089	Plastics products, n.e.c.	0.028	0.1%	1.5%	0.7%
2599	Furniture and fixtures, n.e.c.	0.024	12.5%	63.9%	10.0%
3714	Motor vehicle parts and accessories	0.023	6.5%	142.9%	3.1%
2711	Newspapers	0.022	0.0%	0.0%	0.0%
3711	Motor vehicles and car bodies	0.017	0.0%	0.0%	0.0%
3312	Blast furnaces and steel mills	0.016	10.1%	66.9%	8.1%
1221	Coal and petroleum	0.016	0.0%	0.0%	0.0%
3812	Search and navigation equipment	0.015	0.0%	0.0%	0.0%
3499	Fabricated metal products, n.e.c.	0.014	3.9%	70.7%	5.2%

AD Experience$_j$					
Sector	Description	Experience	Duty	Alternative Duty	Product Coverage
3312	Blast furnaces and steel mills	48	10.1%	66.9%	8.1%
3714	Motor vehicle parts and accessories	12	6.5%	142.9%	3.1%
2869	Industrial organic chemicals, n.e.c.	9	12.5%	67.7%	18.7%
2819	Industrial inorganic chemicals, n.e.c.	9	3.3%	70.7%	3.8%
3494	Valves and pipe fittings, n.e.c.	7	12.5%	117.7%	9.1%
3496	Misc. fabricated wire products	7	6.0%	114.7%	4.0%
2399	Fabricated textile products, n.e.c.	7	5.0%	59.8%	2.0%
3999	Manufacturing industries, n.e.c.	7	1.8%	54.2%	3.3%
3991	Brooms and brushes	6	25.9%	189.6%	13.4%
3011	Tires and inner tubes	6	10.2%	61.1%	5.3%

The table lists the top-10 SIC4 sectors with the highest average value of *Swing Industry*$_{j,T}$ during 1988-2016 (top panel) and the highest value of *AD Experience*$_j$ in 1980-1987 (bottom panel), with the average corresponding AD measures.

Table A-9

First-stage and reduced-form results for Table 4

	First-stage results	Reduced-form results
	(1)	(2)
$\Delta IV_{j,T}$	0.067***	-0.011
	(0.013)	(0.097)
$\Delta Swing\ Industry_{j,T}$	-0.479	-1.856
	(0.337)	(2.510)
SIC4 FE	Yes	Yes
Year FE	Yes	Yes
Observations	2,833	2,833
Adjusted R^2	0.014	0.39

Column 1 (column 2) of the table reports the first-stage (reduced-form) results of the 2SLS estimates in column 1 of Table 4. The sample covers 1988-2016 and comprises all tradable sectors. Observations are weighted by 1988 employment. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-10

The impact of tariffs on employment along supply chains (OLS)

	Tradable sectors		All sectors	
	(1)	(2)	(3)	(4)
$\Delta Direct\ Tariff\ Exposure_{j,T}$	-0.236	-0.218		
	(0.150)	(0.144)		
$\Delta Downstream\ Tariff\ Exposure_{j,T}$		-0.436	-3.689*	-3.402*
		(1.020)	(2.035)	(1.931)
$\Delta Upstream\ Tariff\ Exposure_{j,T}$		-1.255	-3.813***	-3.380***
		(0.922)	(1.281)	(1.293)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,833	2,833	3,351	3,351
Adjusted R^2	0.39	0.39	0.48	0.48

The table reports OLS estimates. The dependent variable $\Delta L_{j,T}$ is the log change in employment in SIC4 industry j during term T. The tariff variables capture changes in the exposure to AD protection, as measured by equations (2) and (3). $\Delta Downstream\ Tariff\ Exposure_{j,T}$ and $\Delta Upstream\ Tariff\ Exposure_{j,T}$ are constructed incorporating higher-order input-output linkages. The coefficients of the indirect $\Delta Swing\ Industry$ variables included in (10) are not reported. The sample covers 1988-2016. In columns 1 and 2 (3 and 4), it comprises tradable sectors (all sectors). Observations are weighted by 1988 employment. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-11

The impact of protection on employment along supply chains
(tariff exposure measures weighted by import penetration)

	Manufacturing sectors		All sectors	
	(1)	(2)	(3)	(4)
Δ*Direct Tariff Exposure*$_{j,T}$	-0.099	-0.189		
	(0.094)	(0.141)		
Δ*Downstream Tariff Exposure*$_{j,T}$		-1.371***	-2.206***	-1.952***
		(0.399)	(0.536)	(0.458)
Δ*Upstream Tariff Exposure*$_{j,T}$		-0.524	-0.182	-0.149
		(0.387)	(0.363)	(0.299)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,742	2,742	3,351	3,351
KP F-statistic	74.9	10.1	30.5	29.0

The table reports 2SLS estimates. The dependent variable $\Delta L_{j,T}$ is the log change in employment in SIC4 industry j during term T. The tariff variables capture changes in the exposure to AD protection. They are constructed by weighting AD duties in (1)-(3) by the corresponding import-penetration ratios and are instrumented using changes in the corresponding IV variables. Δ*Downstream Tariff Exposure*$_{j,T}$ and Δ*Upstream Tariff Exposure*$_{j,T}$ are constructed incorporating higher-order input-output linkages. In columns 2-3 (column 4), we exclude (include) the diagonal of the input-output matrix. The coefficients of the direct and indirect Δ*Swing Industry* variables included in (8)-(10) are not reported. The sample covers 1988-2016. In columns 1 and 2 (3 and 4), it comprises manufacturing sectors (all sectors). Observations are weighted by 1988 employment. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-12

The impact of protection on employment along supply chains (alternative AD measures)

	Alternative Duty	Product coverage	All TTBs	Direct linkages
	(1)	(2)	(3)	(4)
Δ*Downstream Tariff Exposure*$_{j,T}$	-2.752***	-0.252***	-28.067***	-27.154***
	(0.734)	(0.066)	(6.870)	(7.261)
Δ*Upstream Tariff Exposure*$_{j,T}$	0.426	0.036	2.080	0.281
	(0.799)	(0.083)	(5.871)	(7.509)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,351	3,351	3,351	3,351
KP F-statistic	35.8	18.0	79.0	32.8

The table reports 2SLS estimates. The dependent variable $\Delta L_{j,T}$ is the log change in employment in SIC4 industry j during term T. The variables Δ*Downstream Tariff Exposure*$_{j,T}$ and Δ*Upstream Tariff Exposure*$_{j,T}$ capture changes in the exposure to AD protection in vertically-related industries, as measured by (2) and (3), instrumented using changes in the corresponding IV variables. They are constructed including the diagonal of the input-output matrix. In columns 1-2, they are based on alternative measures of AD protection (*Alternative Duty*$_{i,T}$, *Product Coverage*$_{i,T}$), accounting for higher-order input-output linkages; in column 3, they include all TTBs (AD duties, countervailing duties, and safeguards), accounting for higher-order input-output linkages; in column 4, they are based on our main measure of AD protection (*Duty*$_{i,T}$), using only direct (first-order) input-output linkages. The coefficients of the direct and indirect Δ*Swing Industry* variables included in (8) and (10) are not reported. The sample covers 1988-2016 and comprises all sectors. Observations are weighted by 1988 employment. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-13

The impact of protection on employment along supply chains (long differences)

	Tradable sectors	All sectors
	(1)	(2)
Δ*Direct Tariff Exposure*$_{j,T}$	-0.304	
	(1.758)	
Δ*Downstream Tariff Exposure*$_{j,T}$		-32.657***
		(11.553)
Δ*Upstream Tariff Exposure*$_{j,T}$		9.647
		(6.339)
SIC4 FE	Yes	Yes
Period FE	Yes	Yes
Observations	1,214	1,436
KP F-statistic	26.0	16.7

The table reports 2SLS estimates. The dependent variable $\Delta L_{j,T}$ is the log change in employment in SIC4 industry j during period T. The tariff variables capture changes in the exposure to AD protection, as measured by (1)-(3), instrumented using changes in the corresponding IV variables. Δ*Downstream Tariff Exposure*$_{j,T}$ and Δ*Upstream Tariff Exposure*$_{j,T}$ are constructed incorporating higher-order input-output linkages and include the diagonal of the input-output matrix. The coefficients of the swing industry variables included in specifications (8) and (10) are not reported. The sample covers 1992-2016. In column 1 (2), it comprises tradable sectors (all sectors). Observations are weighted by 1988 employment. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-14

Top-10 affected sectors, by number of jobs lost due to input protection (1992-2016)

SIC4	SIC4 description	Employment loss
1510	Construction	243,972
5812	Eating and drinking places	210,493
5210	Retail trade	174,294
5012	Wholesale trade	98,665
8060	Hospitals	64,338
7532	Auto repair	54,170
2752	Commercial printing, lithographic	38,851
8320	Social services	38,142
3714	Motor vehicle parts and accessories	31,696
4210	Trucking	31,358

The table lists the ten SIC4 sectors that suffered the largest predicted job losses due to AD protection against China during 1992-2016. Columns 1 and 2 list the SIC codes of these sectors and the corresponding description. Column 3 reports the counterfactual number of job losses, computed applying equation (11) to the estimates of Table A-13.

Table A-15

The impact of tariffs on employment along supply chains
(production and non-production workers, wages)

	Production		Non-production		Wages	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ*Direct Tariff Exposure*$_{j,T}$	-0.187	-0.633	-0.683	-0.927	0.707**	0.547*
	(1.461)	(1.497)	(0.935)	(0.996)	(0.282)	(0.285)
Δ*Downstream Tariff Exposure*$_{j,T}$		-13.035***†		-12.073**†		-1.426
		(4.791)		(4.828)		(1.395)
Δ*Upstream Tariff Exposure*$_{j,T}$		1.270		-0.295		1.993
		(8.390)		(5.721)		(1.678)
SIC4 FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,704	2,704	2,704	2,704	2,704	2,704
KP F-statistic	45.1	12.7	45.1	12.7	45.1	12.7

The table reports 2SLS estimates. In columns 1-2 (3-4), the dependent variable is the log change in the number of production jobs (non-production jobs) in SIC4 industry j during term T; in columns 5-6, it is the log change in wages in that industry. The tariff variables capture changes in the exposure to AD protection, as measured by (1)-(3), instrumented using changes in the corresponding IV variables. Δ*Downstream Tariff Exposure*$_{j,T}$ and Δ*Upstream Tariff Exposure*$_{j,T}$ are constructed incorporating higher-order input-output linkages, excluding the diagonal of the input-output matrix. The coefficients of the direct and indirect Δ*Swing Industry* variables included in (8)-(9) are not reported. The sample covers 1988-2016 and includes only manufacturing sectors. Observations are weighted by 1988 employment. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively. † indicates that the coefficient is robust to the Romano-Wolf correction.

Table A-16

The impact of protection on employment along supply chains
(SIC2 clusters)

	Tradable sectors		All sectors	
	(1)	(2)	(3)	(4)
Δ*Direct Tariff Exposure*$_{j,T}$	-0.162	-1.014		
	(1.673)	(1.947)		
Δ*Downstream Tariff Exposure*$_{j,T}$		-22.396**	-28.716***	-26.496***
		(8.248)	(10.460)	(8.875)
Δ*Upstream Tariff Exposure*$_{j,T}$		1.292	-0.894	1.807
		(6.335)	(5.889)	(6.009)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,833	2,833	3,351	3,351
KP F-statistic	25.3	6.91	52.9	84.5

The table reports the 2SLS estimates. The dependent variable $\Delta L_{j,T}$ is the log change in employment in SIC4 industry j during term T. The tariff variables capture changes in the exposure to AD protection, as measured by (1)-(3), instrumented using changes in the corresponding IV variables. Δ*Downstream Tariff Exposure*$_{j,T}$ and Δ*Upstream Tariff Exposure*$_{j,T}$ are constructed incorporating higher-order input-output linkages. In columns 2-3 (column 4), we exclude (include) the diagonal of the input-output matrix. All specifications control for the corresponding changes in US MFN tariffs and in Chinese AD duties against the United States. The coefficients of the direct and indirect Δ*Swing Industry* variables included in (8)-(10) are not reported. The sample covers 1988-2016. In columns 1 and 2 (3 and 4), it comprises tradable sectors (all sectors). Observations are weighted by 1988 employment. Standard errors are clustered at the SIC2 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-17

The impact of protection on employment along supply chains (alternative industry fixed effects)

	Tradable sectors		All sectors		Tradable sectors		All sectors	
Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ*Direct Tariff Exposure*$_{j,T}$	-1.177	-1.587			-1.073	-1.891		
	(2.006)	(1.880)			(2.038)	(2.154)		
Δ*Downstream Tariff Exposure*$_{j,T}$		-16.035***	-19.214***	-18.129***		-24.843***	-29.966***	-27.771***
		(5.216)	(6.571)	(5.932)		(6.659)	(7.924)	(6.960)
Δ*Upstream Tariff Exposure*$_{j,T}$		1.489	0.442	1.443		-0.307	-1.376	1.065
		(5.344)	(6.527)	(5.334)		(5.871)	(6.598)	(5.831)
Industry FE	-	-	-	-	Broad	Broad	Broad	Broad
Term FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,833	2,833	3,351	3,351	2,833	2,833	3,351	3,351
KP F-statistic	20.2	6.52	50.5	77.1	17.7	5.48	51.6	75.8

	Tradable sectors		All sectors		Tradable sectors		All sectors	
Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ*Direct Tariff Exposure*$_{j,T}$	-1.016	-1.863			-0.328	-1.158		
	(1.972)	(2.110)			(1.523)	(1.607)		
Δ*Downstream Tariff Exposure*$_{j,T}$		-24.384***	-29.598***	-27.508***		-22.450***	-28.812***	-26.548***
		(6.545)	(7.671)	(6.784)		(6.194)	(7.512)	(6.597)
Δ*Upstream Tariff Exposure*$_{j,T}$		0.233	-1.139	1.113		1.533	-0.580	1.920
		(5.852)	(6.419)	(5.752)		(5.345)	(6.219)	(5.582)
Industry FE	SIC2	SIC2	SIC2	SIC2	SIC3	SIC3	SIC3	SIC3
Term FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,833	2,833	3,351	3,351	2,833	2,833	3,351	3,351
KP F-statistic	18.8	5.71	52.1	78.3	25.4	7.20	63.0	90.2

The table reports 2SLS estimates. The dependent variable $\Delta L_{j,T}$ is the log change in employment in SIC4 industry j during term T. The tariff variables capture changes in the exposure to AD protection. The variables Δ*Downstream Tariff Exposure*$_{j,T}$ and Δ*Upstream Tariff Exposure*$_{j,T}$ capture changes in the exposure to AD protection in vertically-related industries, as measured by (2) and (3), instrumented using changes in the corresponding IV variables. Δ*Downstream Tariff Exposure*$_{j,T}$ and Δ*Upstream Tariff Exposure*$_{j,T}$ are constructed incorporating higher-order input-output linkages. In columns 2-3 and 5-6 (columns 4 and 7), we exclude (include) the diagonal of the input-output matrix. The coefficients of the direct and indirect Δ*Swing Industry* variables included in (8)-(10) are not reported. The regressions include direct and indirect *Experience* variables (coefficients not reported). The sample covers 1988-2016. In columns 1-2 and 5-6 (3-4 and 7-8), it comprises manufacturing sectors (all sectors). Observations are weighted by 1988 employment. In Panel A, there are no industry fixed effects (columns 1-4) and broad (10 one-digit manufacturing sectors, and 1 non-manufacturing sector) industry fixed effects (columns 5-8). In Panel B, there are industry fixed effects at the SIC2 level (columns 1-4) and SIC3 level (columns 5-8). Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-18

The impact of tariffs on employment along supply chains
(extending the analysis to measures introduced during Trump's presidency)

	AD only	All tariffs	Retaliation
	(1)	(2)	(3)
Δ*Downstream Tariff Exposure*$_{j,T}$	-25.490***	-28.181**	-27.472**
	(6.632)	(12.899)	(12.378)
Δ*Upstream Tariff Exposure*$_{j,T}$	0.342	0.264	1.538
	(4.795)	(7.346)	(6.314)
Δ*Downstream Retaliation*$_{j,T}$			-0.600*
			(0.313)
Δ*Upstream Retaliation*$_{j,T}$			0.050
			(0.069)
Observations	3,829	3,829	3,829
KP F-statistic	91.5	1.83	1.87

The table reports 2SLS estimates. The dependent variable $\Delta L_{j,T}$ is the log change in employment in SIC4 industry j during term T. The tariff variables capture changes in the exposure to AD protection, as measured by equations (2) and (3). Δ*Downstream Tariff Exposure*$_{j,T}$ and Δ*Upstream Tariff Exposure*$_{j,T}$ are constructed incorporating higher-order input-output linkages. In column 1, these variables are constructed based on US AD duties against China, while in columns 2-3 they include all TTBs (AD, CVDs, safeguards) applied against China and the additional tariffs introduced during Trump's presidency. Column 3 also controls for retaliatory tariffs. The coefficients of the direct and indirect Δ*Swing Industry* variables included in (10) are not reported. The sample covers 1988-2018 and comprises all sectors. Observations are weighted by 1988 employment. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-19

The impact of protection on employment along supply chains (controlling for additional tariffs)

	Tradable sectors		All sectors	
	(1)	(2)	(3)	(4)
Δ*Direct Tariff Exposure*$_{j,T}$	-0.157	-1.073		
	(1.445)	(1.528)		
Δ*Downstream Tariff Exposure*$_{j,T}$		-21.945***	-26.919***	-24.923***
		(6.286)	(7.321)	(6.420)
Δ*Upstream Tariff Exposure*$_{j,T}$		1.259	-0.766	1.626
		(5.299)	(5.524)	(5.099)
Δ*Direct MFN Exposure*$_{j,T}$	0.058	-0.036		
	(0.121)	(0.114)		
Δ*Downstream MFN Exposure*$_{j,T}$		1.420	-1.347	-1.121
		(1.179)	(1.617)	(1.491)
Δ*Upstream MFN Exposure*$_{j,T}$		1.272*	0.021	0.305
		(0.757)	(1.347)	(1.217)
Δ*Direct Retaliation*$_{j,T}$	-0.018*	-0.017***		
	(0.011)	(0.006)		
Δ*Downstream Retaliation*$_{j,T}$		-0.012	0.004	-0.008
		(0.106)	(0.094)	(0.072)
Δ*Upstream Retaliation*$_{j,T}$		-0.039**	-0.028	-0.029
		(0.017)	(0.020)	(0.019)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,833	2,833	3,351	3,351
KP F-statistic	26.4	7.61	73.4	87.9

The table reports 2SLS estimates. The dependent variable $\Delta L_{j,T}$ is the log change in employment in SIC4 industry j during term T. The tariff variables capture changes in the exposure to AD protection, as measured by (1)-(3), instrumented using changes in the corresponding IV variables. Δ*Downstream Tariff Exposure*$_{j,T}$ and Δ*Upstream Tariff Exposure*$_{j,T}$ are constructed incorporating higher-order input-output linkages. In columns 2-3 (column 4), we exclude (include) the diagonal of the input-output matrix. All specifications control for the corresponding changes in US MFN tariffs and in Chinese AD duties against the United States. The coefficients of the direct and indirect Δ*Swing Industry* variables included in (8)-(10) are not reported. The sample covers 1988-2016. In columns 1 and 2 (3 and 4), it comprises tradable sectors (all sectors). Observations are weighted by 1988 employment. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-20

The impact of protection and import competition on employment along supply chains

	Manufacturing sectors			All sectors
	(1)	(2)	(3)	(4)
Δ*Direct Tariff Exposure*$_{j,t}$	-1.301		-1.640	
	(2.220)		(2.155)	
Δ*Downstream Tariff Exposure*$_{j,t}$				-34.400***
				(4.923)
Δ*Upstream Tariff Exposure*$_{j,t}$				3.091
				(4.089)
Δ*Direct Import Exposure*$_{j,t}$		-0.008***	-0.007***	
		(0.002)	(0.002)	
Δ*Downstream Import Exposure*$_{j,t}$				-0.021
				(0.023)
Δ*Upstream Import Exposure*$_{j,t}$				-0.020***
				(0.007)
Broad Industry FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
Observations	784	784	784	958
KP F-statistic	22.1	45.8	10.7	15.6

The table reports 2SLS estimates. The dependent variable $\Delta L_{j,t}$ is the log change in employment in SIC4 industry j during period t. The tariff variables capture changes in the exposure to AD protection, as measured by (1)-(3), instrumented using changes in the corresponding IV variables. Δ*Direct Import Exposure*$_{j,t}$, Δ*Downstream Import Exposure*$_{j,t}$, and Δ*Upstream Import Exposure*$_{j,t}$ capture changes in exposure to import competition from China, instrumented with the growth of imports from China in eight other high-income countries (excluding the United States). The downstream and upstream exposure variables are constructed incorporating higher-order input-output linkages and include the diagonal of the input-output matrix. The coefficients of the direct and indirect Δ*Swing Industry* variables included in (8) and (10) are not reported. The sample covers 1991-2011. In columns 1-3 (column 4), it includes only manufacturing sectors (all sectors). Observations are weighted by 1988 employment. We include broad industry dummies (10 one-digit manufacturing sectors, and 1 non-manufacturing sector). Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.