Trade Protection along Supply Chains*

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Abstract

During the last few decades, the United States has applied increasingly high antidumping (AD) duties on imports from China. We combine detailed information on these duties with US input-output data to study the effects of trade protection along supply chains. To deal with endogeneity concerns, we instrument tariffs exploiting variation in the political importance of industries – resulting from changes in the identity of swing states across electoral terms – and in their historical experience at petitioning for AD. We find that tariffs in upstream industries have large negative effects on downstream industries, raising input prices and decreasing employment, sales, and investment. Our baseline estimates for the last seven complete presidential terms (1988-2016) indicate that around 570,000 US jobs were lost in downstream industries due to AD duties against China in upstream industries. When we extend the analysis to protectionist measures introduced under Trump's presidency, we find that almost 200,000 jobs were lost in downstream industries in the first two years of his term.

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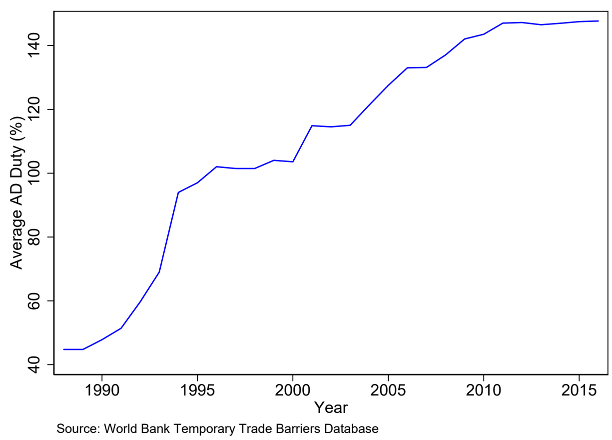
Since the beginning of 2018, the Trump administration has introduced a series of tariff measures to limit trade with China, triggering retaliation. The trade war between the United States and China has stimulated several studies on the effects of this "return to protection" (e.g. Amiti *et al.*, 2019b; Bellora and Fontagné, 2019; Cavallo, *et al.*, 2019; Flaaen and Pierce, 2019; Fajgelbaum *et al.*, 2020; Flaaen *et al.*, 2020). However, well before President Donald Trump took office, the US had already been targeting China through antidumping (AD) duties, its most frequently used trade barrier. As shown in Figure 1, between the start of the presidency 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 (from 44.8% to 147.7%).[1]

Figure 1

Average US AD duty against China (1988-2016)



Notes: The figure plots the average AD duty applied by the US on imports from China. Source: Authors' calculations based on an extended version of the Temporary Trade Barriers Database.

The last few decades have also witnessed the emergence of global supply chains and the rise of trade in intermediate goods, which now accounts for as much as two-thirds of international trade (Johnson and Noguera, 2012). In a world in which production processes are fragmented across countries, the effects of tariffs propagate along supply chains, with firms in downstream industries suffering from protection upstream. 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."[2] Such concerns are exacerbated by

[1]During the same period, the share of Chinese imports covered by US AD duties has also dramatically increased (from 1.1% in 1991 to 7.1% in 2016).

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

the fact that protection is often targeted towards intermediate inputs. As shown in Figure A-1 in the Appendix, the share of Chinese imports of intermediate goods covered by US AD duties and other temporary trade barriers (TTBs) has been steadily increasingly relative to the corresponding share for consumption goods.[3]

The goal of this paper is to study the effects of protection along supply chains. As pointed out by Trefler (1993), a key challenge to identify the effects of tariff changes is the endogeneity of trade policy. When studying the impact of tariffs along supply chains, a major concern is that 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, higher tariffs on some inputs (e.g. steel or car parts) can hurt firms in vertically-related industries (e.g. construction companies, car manufacturers), even if they are sourcing these inputs domestically.[4] These firms will then try to lobby against high tariffs on their inputs, particularly if they stand to lose a lot from protection (e.g. Gawande *et al.*, 2012; Mayda *et al.*, 2018). If successful, these lobbying efforts would make it harder to identify the negative effects of protection along supply chains.[5] As discussed in Section 3, other potential omitted variables, such as positive productivity shocks experienced by domestic downstream producers or foreign input suppliers, can have similar effects.

To deal with endogeneity concerns, we follow an instrumental variable (IV) approach. Our instrument builds on Trimarchi (2020) and exploits exogenous variation in supply and demand for protection. On the supply side, several studies show that US AD duties respond to domestic political interests (e.g. Finger *et al.*, 1982; Moore, 1992; Hansen and Prusa, 1997; Aquilante, 2018). There is also evidence that US trade policy is 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). We exploit exogenous variation in the supply for AD protection, resulting from cross-sectoral variation in the importance of industries across states and time variation in the identity of swing states.

On the demand side, we exploit variation across industries in their experience at filing

[3]Similar patterns emerge when looking at TTBs applied during the last few decades by the United States against other countries, as well as TTBs applied by other advanced economies (Bown, 2018). In the recent trade war with China, US tariffs are also skewed towards intermediate inputs, such as primary metals, machinery, computer products, and electrical equipment (Fajgelbaum *et al.*, 2020).

[4]As shown by Amiti *et al.* (2019a), higher tariffs increase the price charged not only by foreign exporters, but also by domestic import-competing producers. This is also what we find when looking at the effects of AD duties on the price of imported and domestically-produced inputs (see Section 5).

[5]For example, 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" (*Wall Street Journal*, December 16, 2006).

AD petitions. Previous studies show 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). Following this idea, we use information on AD petitions filed by US industries before our sample period to construct a measure of an industry's ability to request protection.[6]

The logic of the instrument is that the most protected industries in a given electoral term should be those that are more important in swing states and that can exploit this political advantage thanks to their knowledge of the complex US legal and institutional AD procedures. Combining the two components improves the power of the instrument, allowing us to better predict the observed variation in protection.

We collect detailed information on all temporary trade barriers (TTBs) applied by the US during the last decades. In our main analysis, we focus on AD duties applied against China during the last seven complete presidential terms covering the 1988-2016 period. AD is by far the most common TTB used during this period (see Figure A-2).[7] In robustness checks, we extend the analysis to other TTBs and to other tariffs introduced since President Trump took office.[8]

To study the effects of trade protection along supply chains, we combine the information about tariffs with disaggregated US input-output data, which allows us to identify vertical linkages between 479 industries and construct different measures of input protection.

We show that input tariffs have a negative impact on downstream industries, in terms of employment, sales, and investment. Our empirical results emphasize the importance of dealing with the endogeneity of trade policy. If we ignore this concern, we generally find no significant effect of tariffs along supply chains. When instead we instrument for trade policy, we find that higher input tariffs have large negative effects on downstream industries,

[6]During the 1980s, legal and institutional changes in AD proceedings made it easier to file for AD protection (Irwin, 2005, 2017). However, there is important cross-sectoral variation in the number of AD cases initiated during this period. The higher number of petitions were filed by industries that at the time were exposed to strong import competition from Japan (e.g. automotive, steel, electronics) and were not protected by other protectionist policies (e.g. Multi-Fibre Arrangement).

[7]WTO rules allow member countries to use three forms of TTBs: AD duties, countervailing duties, and safeguards. Antidumping duties are tariffs that can be imposed when a product is sold by a foreign firm below a "fair value", that is below the price charged in their domestic market or, alternatively, below the production cost. Countervailing duties are tariffs that can be introduced when foreign producers benefit from illegal subsidies provided by their government. Safeguards are special measures that can be introduced when a surge in imports cause, or threaten to cause, domestic market disruption, even in the absence of unfair behavior by a foreign firm or government.

[8]Our results are also robust to controlling for applied most-favored-nation (MFN) tariffs. We do not include these tariffs in our benchmark analysis, since there is little variation during our sample period. We can also extend the analysis to other countries that have been the target of US AD protection.

leading to a significant decline in the growth rate of employment (affecting both blue-collar and white-collar workers), sales and investment.

We also provide evidence for the mechanism behind the negative effects of tariffs along supply chains. We show that AD duties increase the price of both imported and domestically produced inputs. Thus, higher tariffs in upstream industries increase production costs for firms in downstream industries, independently of whether they source the protected inputs from foreign or domestic suppliers.

In terms of magnitude, our baseline estimates indicate that a one standard deviation increase in the average input tariff decreases the growth rate of employment by 0.4 percentage points, which explains 23% of the observed average annual employment growth during our sample period. When considering all downstream industries, our estimates imply that around 570,000 jobs were lost due to AD duties against China. The effects are smaller (around 110,000 jobs) if we restrict the analysis to manufacturing downstream industries. When we extend the analysis to the protectionist measures introduced since Trump took office, we find that around 185,000 jobs were lost across all downstream industries during the first two years of his presidency.

Combining our results with Trimarchi's (2020) shows that tariffs destroy many more jobs than they protect. His estimates for 1988-2016 suggest that AD duties against China saved around 22,000 manufacturing jobs in protected industries. Our estimates show that these are less than 5% of the jobs destroyed by the same tariffs in the rest of the economy.

The rest of the paper is structured as followed. In Section 1 we briefly review the related literature. In Section 2, we describe the data and variables used in our empirical analysis. Section 3 discusses the identification strategy. Sections 4-6 present the empirical results. Section 7 concludes.

1 Related Literature

Our paper is related to three main streams of literature.

First, as mentioned in the introduction, the ongoing US-China trade war has motivated several recent papers on the effects of protection. Amiti *et al.* (2019b) study the impact of the US-China trade war on prices and welfare. Using monthly 10-digit Harmonized Schedule (HS) product-level data on tariff-inclusive prices at the US border, 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.[9] They further show that tariffs changed the pricing behavior of U.S. producers by protecting them from foreign competition and enabling them to raise prices and markups. These results suggest that higher tariffs in upstream industries increase production costs for firms in downstream industries, independently of whether they source the protected inputs domestically or from foreign suppliers.[10]

Bellora and Fontagné (2019) use a Computable General Equilibrium model which differentiates goods according to their use (for final or intermediate consumption) to study the impact of the US-China trade war. Flaaen and Pierce (2019) find that the tariffs introduced by the Trump Administration in 2018 and 2019 drove up the cost of inputs for American manufacturers, and combined with retaliation by trading partners, destroyed manufacturing jobs. Similarly, Flaaen *et al.* (2020) find significant price effects due to US import restrictions on washing machines.

Our analysis differs from the the above-mentioned studies of the US-China trade war in several important ways. First, we study the effects of protectionism on a much longer time horizon, exploiting the striking increase in AD duties against China since the late 1980s, rather than restricting the analysis to the Trump era. Second, we study the effects of protection along supply chains, considering the entire US economy, rather than restricting the analysis to downstream manufacturing industries. Finally, we employ an instrumental variable approach to deal with concerns about the endogeneity of trade policy.

The second stream of literature we build on is on global sourcing. Various studies have emphasized the productivity-enhancing effects of input trade and input 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. Yi, 2003; Blanchard *et al.*, 2016; Erbahar and Zi, 2017; Conconi *et al.*, 2018; Vandenbussche and Viegelahn, 2018; Barattieri and Cacciatore, 2019; Bown *et al.*, 2020). We contribute to this literature by exploiting a rich dataset covering all temporary tariff barriers introduced by the US during 1980-2019 and employing an instrumental variable approach to deal with concerns about the endogeneity of trade policy.

Finally, our empirical strategy builds on the literature on the political economy of trade policy, and in particular on studies that have focused on antidumping duties and other

[9] This complete pass-through result is also supported by other studies (e.g. Cavallo *et al.*, 2019; Fajgelbaum *et al.*, 2020).

[10] Consistent with this reasoning, De Loecker *et al.* (2016) find substantial declines in domestic good prices due to trade liberalization in India.

temporary trade barriers (e.g. Finger *et al.*, 1982; Moore, 1992; Hansen and Prusa, 1997; Bown and Crowley, 2013; Blonigen and Prusa, 2016; Aquilante, 2018). The closest paper in this literature is Trimarchi (2020), on which our identification strategy is built. He studies the impact of AD duties on protected industries (in terms of imports and employment) during the 1988-2016 period. We examine instead the impact of tariffs along supply chains, consider additional outcomes (e.g. input prices, sales, and investment), and extend the sample period to include measures introduced during the Trump's presidency.

2 Data and Variables

To carry out our empirical analysis, we combine three types of data: US input-output tables, which allow us to identify industries that are linked along supply chains; detailed information on trade barriers introduced by the United States since the 1980s, which allows us to measure variation in protection across industries and over time; and industry-level data such as employment to study the effects of upstream protection on downstream industries. In what follows, we describe these data and the key variables used in our empirical analysis.

2.1 Data on Input-Output Linkages

A 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 trace upstream and downstream linkages between industries. Following Acemoglu *et al.* (2016), we employ the 1992 Use of Commodities by Industries After Redefinitions (Producers' Prices) tables. 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 identify linkages between 479 industries, including both manufacturing and non-manufacturing (e.g. construction, services). 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).

For every pair of industries, ij, the input-output accounts provide the dollar value of i required to produce a dollar's worth of j. We denote with $\omega_{i,j}$ the direct requirement coefficient for the sector pair ij, i.e. the dollar value of i used as an input in the production of one dollar of j. In our baseline regressions, we use this variable to capture direct vertical linkages between industries. In robustness checks, we use total requirements coefficients, denoted with $\theta_{i,j}$, which take into account indirect linkages.[11]

Panels (a) and (b) of Figure A-3 illustrate the average $\omega_{i,j}$ across all SIC4 j industries, focusing respectively on the top-10 and top-50 most important inputs (i.e. with the highest $\omega_{i,j}$). Notice that the distribution of input-output linkages is highly skewed, with the most important input accounting for a much larger cost share.

2.2 Data on Tariffs

Antidumping Duties and Other Temporary Trade Barriers

The second source of information of tariff 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 products under investigation.

For cases initiated by the US, we can identify all the products covered at the 6-digit level of the Harmonized System (HS6).[12] We convert the tariff data from the HS6 classification into the SIC4 classification to be able to identify input-output linkages and investigate the impact of protectionist measures on industry-level outcomes.[13]

In our main empirical analysis, we focus on AD duties introduced by the US against China.[14] During the seven presidential terms covering 1988-2016, the US has initiated 185 cases in which China was accused of dumping. In 74% of those cases, the US has imposed measures on Chinese products. In robustness checks, we consider other protectionist mea-

[11]Total requirements coefficients show the sum of direct and indirect purchases required to produce a dollar of output. Indirect purchases necessary to produce a car, for example, include the aluminum used in the frame and engine, as well as the electricity necessary to produce the aluminum.

[12]For US cases initiated between 1980 and 1988, the product information is at the 5-digit level of the Tariff Schedule of the United States Annotated (TSUSA), while for cases initiated after 1988 it is at the 10-digit level of the Harmonized Tariff Schedule (HTS). We concord TSUSA and HTS codes into HS6 codes. See Trimarchi (2020) for more details on the matching procedure.

[13]We harmonize HS codes over time to the HS 1992 nomenclature, using the concordance tables provided by the United Nations Statistics Division. We then concord HS6 codes to SIC4 codes, following the procedure of Autor *et al.* (2013).

[14]Note that the level of the AD duty might differ across targeted firms. We use the "all others" AD rate which is applied to all firms that are not specifically named in the investigation, and is usually higher than the ones applied to specific firms. Still, our results continue to hold if we use the average AD rate across firms. This is not surprising given the high correlation between the two rates (0.85).

sures and other countries targeted by the United States.[15] The top panel of Table A-1 reports descriptive statistics on US AD duties applied to imports from China during 1988-2016. The average level of the AD duty ($\tau_{i,t}$) is 15%, reaching up to 430%, with a standard deviation of 51%.

Since the start of Trump's presidency in January 2017, the United States has continued to target imports from China, initiating 31 new AD cases, and imposing 32 measures.[16] Figure A-4 shows this recent increase in average AD duties against China, as highlighted by the red solid line. When extending our analysis to the measures introduced under President Trump, we cover the first two years of his term, since industry-level employment is only available until the end of 2018. The bottom panel of Table A-1 reports descriptive statistics on AD duties during 2017-2018, which reveal that AD protection has further increased under Trump with the average AD duty reaching 36%, with a standard deviation of 81%.

MFN tariffs

Even though this paper's focus is on the US' most frequently used temporary trade barrier antidumping, we have also collected data on the US' most-favored-nation (MFN) tariffs that are applied to imports from other GATT/WTO members. 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 renegotiated in a new round of negotiations. Unlike AD duties, they must be applied in a non-discriminatory manner to imports from all countries (Article I of the GATT).

The top panel of Table A-2 reports descriptive statistics on the MFN tariffs applied by the United States since the beginning of our sample period. Comparing these with the corresponding statistics in Table A-1, notice that MFN tariffs are on average much lower than the AD duties applied against China. For example, during the 1988-2016 period, the mean applied MFN tariff ($\tau_{i,t}$) is 5% (instead of 15% for AD duties), though there is still considerable variation (the standard deviation is 21 and the maximum rate is 350%). Within SIC4 industries, there is little variation in US MFN tariffs: during most of our sample period, the rates applied by the United States coincide with the tariff bindings agreed at the end

[15]A case may involve multiple target countries. For instance, in March 2016, the United States imposed AD duties on "Certain uncoated paper" imported from Australia, Brazil, China, Indonesia, and Portugal. Between 1988-2016, 37% of AD petitions named China as one of the target countries (this share jumped to 50% after China's accession to the WTO in December 2001).

[16]Of the new measures, 9 were due to investigations that started before Trump took office.

of the Uruguay Round of multilateral trade negotiations (1986-1994). For this reason, we abstract from changes in MFN tariffs in our benchmark results, and when we include them our estimates of the effects of AD duties are unchanged.

Additional Tariffs under President Trump

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).[17] These were stacked on top of AD duties already applying 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. This can be seen by comparing the statistics reported in the bottom panels of Tables A-1 and A-2: the average special tariff against China in 2018 was 11% (with a standard deviation of 7%), while the average AD duty against China in 2017-2018 was 36% (with a standard deviation of 81%).

2.3 Measures of Input Protection

Combining the input-output data from the BEA with the data on tariffs described above, we construct different variables capturing the degree of input protection faced by downstream industries. Our main measure captures the average level of input protection:

$$\textit{Average Input Tariff}_{j,t} = \sum_{i=1}^{N} \omega_{i,j} \; \tau_{i,t}, \tag{1}$$

where $\omega_{i,j}$ is the cost share of input i in the production of SIC4 good j, and $\tau_{i,t}$ is the average AD duty applied by the US in year t against Chinese imports of good i.[18] Thus, $\sum_{i=1}^{N} \omega_{i,j} \; \tau_{i,t}$

[17] On February 7, the United States introduced safeguard measures on solar panels and washing machines (at 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, it 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.

[18] For a given SIC4 industry i, $\tau_{i,t}$ is the weighted average AD duty applied to the targeted HS6 goods in the industry.

is the average AD duty on inputs faced by downstream industry j. Since tariffs are mostly applied to imports of manufacturing goods, in our baseline regressions the set N includes only the 392 manufacturing sectors.[19]

As mentioned before in Section 2.1, the distribution of vertical linkages is highly skewed (see Figure A-3). For example, when looking at manufacturing inputs, steel (SIC 3312) is the most important input for 18% of the industries (see Table A-3). Our second measure of input tariff captures the level of protection on *key* inputs:

$$\textit{Tariff on Key Input}_{j,t} = \tau_{1,j,t}, \tag{2}$$

where $\tau_{1,j,t}$ is the AD duty applied in year t on Chinese imports of sector j's most important input (with highest $\omega_{i,j}$).

Recall that we rely on the BEA's 1992 input-output tables to identify vertically-related industries. If technology changes over time, this can lead to measurement error in input protection. Notice, however, that concerns about measurement only apply to the average input tariff (1), since our alternative measure (2) relies on IO coefficients solely to identify the key input, which is unlikely to change over time. Moreover, data from the BEA's 1997-2018 IO tables show little variation in the $\omega_{i,j}$ weights. This can be in Figure A-5, in which we have plotted the direct requirement coefficients for 1997 and 2018. The correlation between them is 0.93.

Table A-6 presents descriptive statistics on the two tariff measures above, focusing on the top-10 SIC4 industries with the highest level of input protection. These include SIC 3449 ("Miscellaneous metal work"), 2653 ("Corrugated and solid fiber boxes") and 3711 ("Motor vehicles and car bodies"). Among the key inputs subject to high AD duties are SIC 3312 ("Blast furnaces and steel mills"), 2621 ("Paper mills") for which the average AD duty against China during 1988-2016 was respectively 81.61% and 76.93%.

The variables $\textit{Average Input Tariff}_{j,t}$ and $\textit{Tariff on Key Input}_{j,t}$ capture mostly variation in the intensive margin of protection. In robustness checks, we use four alternative protectionist measures, which capture variation on the extensive margin of input protection. To this purpose, we replace $\tau_{i,t}$ in (1) with the following measures:

> $\textit{Dummy}_{i,t}$: dummy equal to 1 if at least one HS6 good in sector i is protected by an AD duty against China in year t.
>
> $\textit{Count of Products}_{i,t}$: number of HS6 goods in sector i covered by at least one AD duty

[19] The results are robust to including all tradable sectors.

against China in year t;

$Import\ Coverage_{i,t}$: share of imports in sector i covered by at least one AD duty against China in year t;

2.4 Industry-Level Variables

To study the effects of input protection on employment, we follow Acemoglu *et al.* (2016) and use data from the US Census County Business Patterns (CBP), which provide information on industry-level employment up to 2018. The variable $Employment_{j,t}$ measures total employment in SIC4 industry j in year t.

To construct a measure of input prices for each downstream industry, we combine data on prices with input-output coefficients. First, we collect price data on imported and domestically produced goods. We obtain data on import prices from United Nations (UN) Comtrade database, available from 1991. The variable $Import\ Price_{i,t}$ is the unit value of US imports from China of good i in year t.[20] Data on prices of domestically produced goods is from the BLS. The variable $Domestic\ Price_{i,t}$ is the producer price index (PPI) of good i in year t. We normalize both import and domestic prices of each industry to 100 for the year 2000 to create a harmonized price index. Second, we weight the import and domestic price indices with input-output coefficients from the BEA to construct the following variables:

$$Average\ Price\ of\ Imported\ Inputs_{j,t} = \sum_{i=1}^{N} \omega_{i,j}\ Import\ Price_{i,t}, \tag{3}$$

$$Average\ Price\ of\ Domestic\ Inputs_{j,t} = \sum_{i=1}^{N} \omega_{i,j}\ Domestic\ Price_{i,t}. \tag{4}$$

Another source of data is the NBER-CES Manufacturing Industry Database, which allows us to study the effects of tariffs on other industry-level outcomes. These include the variables $Blue\ Collar\ Workers_{j,t}$ and $White\ Collar\ Workers_{j,t}$ (number of blue-collar and white-collar jobs, in thousands), as well as $Sales_{j,t}$ and $Investment_{j,t}$ (in millions of dollars).

[20] 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 price of different HS6 products by their import values in year t.

3 Identification Strategy

3.1 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 when examining the effects of tariff changes. In particular, 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 lobbying. As discussed above, higher tariffs in upstream industries can increase production costs in downstream industries, independently of whether producers import the protected inputs domestically or from foreign suppliers (e.g. Amiti *et al.*, 2019b). Final good producers (e.g. construction companies, car manufacturers) will thus lobby against high tariffs on their inputs (e.g. steel, car parts), particularly if they stand to lose a lot from input protection.[21] If downstream firms successfully lobby against input protection, simple ordinary least squares (OLS) coefficients will be biased upwards, making it harder to identify the negative effects of protection along supply chains.

Similar concerns are raised by other potential omitted variables, including productivity shocks, which can be positively correlated with both the growth of downstream industries and the degree of input protection. Consider, for example a positive productivity shock experienced by foreign input suppliers, which allows them to lower their prices/increase their quality. This shock should benefit US firms in downstream sectors. It can also lead to an increase in input protection: in the case of temporary trade barrier 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. Omitting foreign input productivity shocks would thus work against finding negative effects of tariffs along supply chains.

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

3.2 Instrumental Variable

To deal with these endogeneity concerns, we follow an instrumental variable (IV) approach as in Trimarchi (2020). Our instrument has two components, which exploit exogenous variation in supply and demand for AD protection.

3.2.1 Supply for Protection

The first component of the instrument exploits variation in the supply side of AD protection driven by swing-state politics in the United States.

Several studies show that US trade policies are biased towards the interests of swing states.[22] Mûls and Petropoulou (2013) consider non-tariff barriers (including AD duties) and show that states classified as swing in President Reagan's first term benefited from a 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 affects US MFN tariffs. Fajgelbaum *et al.* (2020) find that the tariffs introduced by Trump in 2018 were targeted toward sectors concentrated in politically competitive counties.

Domestic politics can shape the decisions of the two key institutions involved in AD investigations in the United States: the Department of Commerce (DOC) and the International Trade Commission (ITC). These agencies have the authority granted by Congress to determine, respectively, whether a product has been "dumped" by foreign producers and whether this "unfair practice" has caused material injury to the US industry. The DOC is a part of the executive branch of the federal government.[23] The President nominates the top positions in the department (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).[24] Through these political appointments, the White House can

[22] 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 top trade negotiator), Stephen Byers (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).

[23] In 1980, the DOC replaced the Treasury Department as the institution in charge of dumping investigations. As pointed out by Irwin (2005), "[t]he shift took place because Treasury was perceived to be relatively indifferent to antidumping petitions, whereas Commerce was expected to be a more sympathetic advocate for domestic firms seeking protection."

[24] These appointees must be confirmed by the Senate. Several other 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.

shape AD decisions of the DOC.[25] The ITC is instead a bipartisan agency composed by six commissioners, who are appointed for a non-renewable term of nine years. These commissioners are nominated by the President and confirmed by the Senate, and no more than three commissioners may be from the same political party.

An AD case starts with a petition claiming injury caused by unfair import competition from a specific country.[26] The DOC conducts the dumping investigation, while the ITC is in charge of the injury investigation. In its investigation, the DOC determines whether a product has been sold at "less than the fair value" and computes the "dumping margin." In the material injury investigation, ITC commissioners vote on whether unfair import competition causes (or threatens to cause) harm to the domestic industry. If a majority of commissioners rules affirmatively, an AD duty is introduced equal to the dumping margin established by the DOC in its investigation. In case of tied votes, the decision is considered affirmative. In 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 injury in 68% of the cases.[27]

Several studies have shown that ITC votes reflect the interests of the members of the Finance committee in the Senate and the Ways and Means committee in the House, the two most powerful committees dealing with trade policy in Congress. Moore (1992) find 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 line with the interests of Democratic (Republican) members of the Finance committee. These studies suggest that the Finance and Ways and Means committees can influence AD decisions through various channels, e.g. appointment confirmations, budget allocation, and

[25] In some cases, the executive directly intervenes in these decisions. 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, sent a "Recommendation for Action" letter requesting a minimum 36% import duty (see US Court of International Trade, Consol. Court No. 17-00091).

[26] AD petitions are usually filed by US manufacturing industries. Wholesalers, trade unions, trade or business associations are also entitled to be petitioners, to the extent that they produce or sell a "like" product to the import good that is allegedly dumped. It is also possible for the DOC to initiate an investigation ex-officio, but this has happened in very few instances during our sample period.

[27] 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).

oversight hearings.[28] Interestingly, congressmen from swing states are overrepresented in these powerful committees,[29] which can be one of the reasons why AD protection is skewed in favor of key industries in these states.

The general idea behind the first component of our instrument is that US politicians manipulate AD policy for electoral purposes, influencing decisions by the DOC and the ITC to favor important industries in battleground states. In line with several studies (e.g. Conconi *et al.*, 2017; Ma and McLaren, 2018; Fajgelbaum *et al.*, 2020), we use information on vote shares in previous presidential elections to identify swing states. In particular, the dummy variable $Swing_{s,t}$ classifies a state s to be electorally competitive in year t if the difference in the vote shares of the Democratic and Republican candidates in the previous presidential election is less than 5%.

Figure 2 shows which states are classified as swing, based on votes shares in last eight presidential elections. Notice that both the number and identity of swing states vary significantly across terms.[30] Our identification strategy relies on the assumption that these changes are exogenous to trade policy, i.e. AD duties do not affect whether or not the difference in vote shares between the Democratic and Republican candidates is less than 5%.[31]

To measure the importance of an industry i in swing states in year t, we construct the following variable:

$$Swing\ Industry_{i,t} = \frac{\sum_s L_{s,i}^{1988} \times Swing_{s,t}}{\sum_s \sum_i L_{s,i}^{1988} \times Swing_{s,t}}. \tag{5}$$

This is the ratio of the total number of workers employed in industry i in states that are classified as swing in year t over the total number of workers in tradable sectors in swing

[28] Evidence for this influence can more easily be documented for the ITC (in which votes by individual commissioners are recorded) than for the DOC (for which only the final decision is made public).

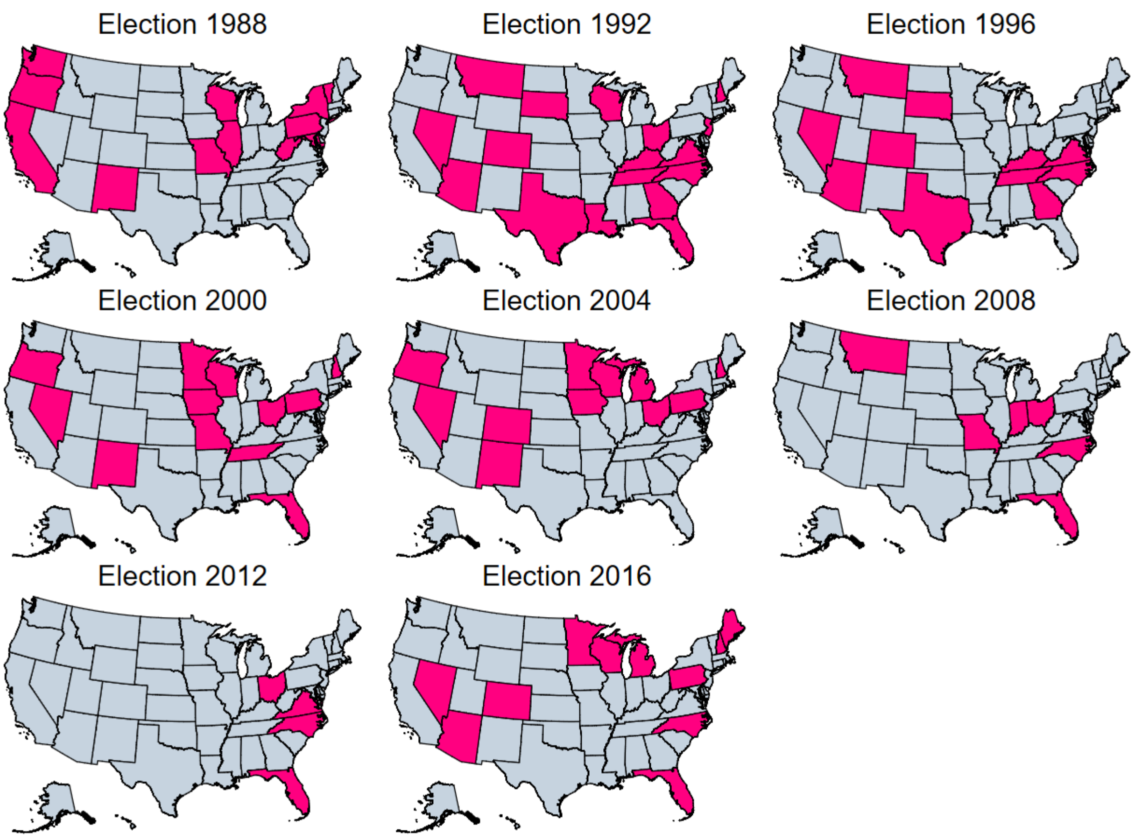
[29] During the eight presidential elections in 1988-2016, swing states accounted for 21% of the number of US states on average (see Figure 2). However, 33% (36%) of the new members of the Senate Finance (House Ways and Means) committee in a presidential term were from states classified as swing.

[30] The swing states are: in 1988, California, Illinois, Maryland, Missouri, New Mexico, New York, Oregon, Pennsylvania, Vermont, Washington, West Virginia, and Wisconsin; in 1992, Arizona, Colorado, Florida, Georgia, Kentucky, Louisiana, Montana, Nevada, New Hampshire, New Jersey, North Carolina, Ohio, South Dakota, Tennessee, Texas, Virginia, and Wisconsin; in 1996, Arizona, Colorado, Georgia, Kentucky, Montana, Nevada, North Carolina, South Dakota, Tennessee, Texas, and Virginia; in 2000, Florida, Iowa, Minnesota, Missouri, Nevada, New Hampshire, New Mexico, Ohio, Oregon, Pennsylvania, Tennessee, and Wisconsin; in 2004, Colorado, Iowa, Michigan, Minnesota, Nevada, New Hampshire, New Mexico, Ohio, Oregon, Pennsylvania, and Wisconsin; in 2008, Florida, Indiana, Missouri, Montana, North Carolina, and Ohio; in 2012, Florida, North Carolina, Ohio, and Virginia; in 2016, Arizona, Colorado, Florida, Maine, Michigan, Minnesota, Nevada, New Hampshire, North Carolina, Pennsylvania, and Wisconsin.

[31] In line with this assumption, Trimarchi (2020) shows that an increase in state-level AD protection during a presidential term has no significant effect on the identity of swing states at the end of that term.

Figure 2

Swing states in US Presidential Elections (1988 to 2016)



Notes: The maps indicate in pink the states classified as swing based on vote shares in the last eight presidential elections.

states. We fix the employment shares at their levels in 1988, the first year of our sample period, to dispel the concern that these shares might be affected by trade protection.[32]

Overall, the variable $Swing\ Industry_{i,t}$ captures exogenous variation in the political importance of an industry: the treatment variable ($Swing_{s,t}$) captures exogenous variation in the political importance of states across terms, driven by changes in the identity of swing states; the initial employment shares ($L_{s,i}^{1988}$) reflect differences in exposure to the treatment across industries, depending on their importance in different states.

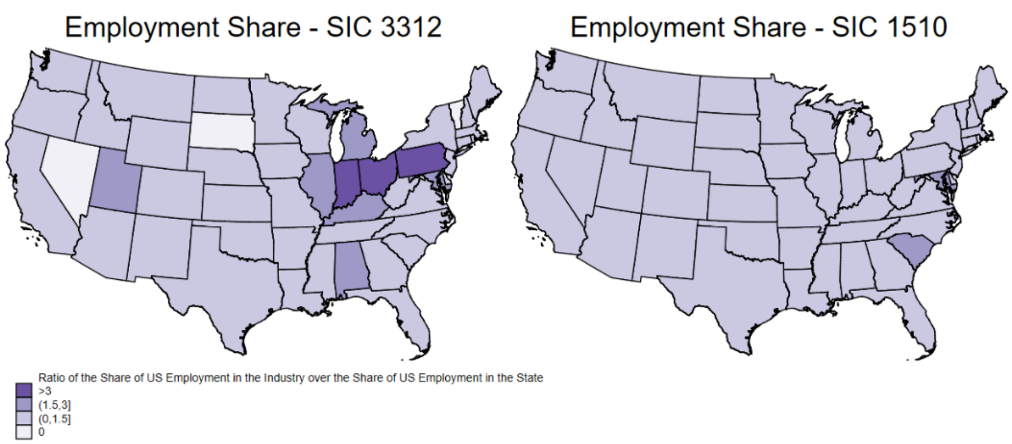
Figure 3 illustrates the geographical distribution across US states of two industries: SIC 3312 ("Blast furnaces and steel mills") and SIC 1510 ("Construction"). Using 1988 CPB data, we have computed the ratios between state-level shares of US employment in these industries and state-level shares of overall US employment. The map on the left is for steel,

[32]Using data from later years would yield very similar results, given that the geographical distribution of industries across states is very stable over time. This can be seen in Figure A-6, in which we have plotted 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.

one of the most heavily protected manufacturing sectors, with an average AD duty of 82% during our sample period. Notice that this sector is highly geographically concentrated: three states in the Rust Belt (Ohio, Pennsylvania, and Indiana) 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.[33] 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). Notice that 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 size of the employment force in the state.[34]

Figure 3

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



Notes: 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.

Figure 3 reflects a general pattern: final good industries are more geographically dispersed than input industries. In fact, we find that 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).[35] When comparing industries based on their position along supply chains, more upstream industries are thus more geographically concentrated.

[33] 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.

[34] 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).

[35] Antràs *et al.* (2012) use the BEA's 2002 input-output table to estimate an industry's average distance from final use and call this "upstreamness." Ellison and Glaeser (1997) use US data to develop an industrial agglomeration index. We have constructed this index for 2002, the same year as the downstream measure.

3.2.2 Demand for Protection

The logic of the second component of the instrument builds on the literature on antidumping protection in the United States. Previous studies show that, due to the legal and institutional complexity of US AD procedures, industries with prior experience in AD cases face lower costs of filing and a higher probability of success in new cases (e.g. Blonigen and Park, 2004; Blonigen, 2006). Following this idea, we use information on AD petitions filed by US industries before our sample period to construct a measure of an industry's ability to request protection.

During the 1980s, legal and institutional changes in AD proceedings made it easier to file for AD protection (Irwin, 2005, 2017). Our experience variable is the count of AD petitions filed by industry i during the 1980-1987 period:

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

This variable is meant to capture exogenous variation in the ability to request AD protection, coming from pre-sample cross-sectoral differences in AD petitions. To ensure exogeneity of the instrument, we exclude petitions targeting China and leading to measures in force after 1987. Based on this measure, 39.5% of the industries filed petitions during the 1980-1987 period. There is important variation on the intensive margin (the variable $Experience_i$ has a mean of 0.73 and a standard deviation of 2.83).[36]

During the 1980s, the United States was in a trade war not with China, but with Japan (Bown and McCulloch, 2009). At the time, Japan was the biggest target of US AD protection and most petitions were filed by US industries that faced strong competition from Japanese imports (e.g. cars, car parts, steel, electronics). In Table A-7 column 1, we regress $Experience_i$ on the log of $Imports_i^{JP}$, the average US imports from Japan during 1980-1987, and find a positive and significant relationship.[37] The coefficient stays positive and significant in column 2 when we include the 10 broad industry fixed effects as defined by Acemoglu *et al.* (2016).

One could be concerned that the experience variable may capture industry characteristics not related to the knowledge of AD procedures. The main suspect is industry concentration. The literature on collective action suggests that free-riding problems may worsen as an

[36] The maximum number of petitions (57) was filed by the steel industry (SIC 3312). In robustness checks, we verify that the results are generally robust to winsorizing the variable $Experience_i$ at the 95$^{\text{th}}$ percentile.

[37] The variable $Imports_i^{JP}$ is constructed using data from Bernard *et al.* (2006). These results are robust to using average US import penetration rates from Japan instead.

industry gets less concentrated (e.g. Olson, 1965; Bergstrom *et al.*, 1986; Bombardini and Trebbi, 2012). Firms in more concentrated industries may thus find it easier to cooperate when filing AD petitions. If this is the case, variation in $Experience_i$ may reflect differences across industries in their ability to solve collective action problems. Other variables may also be correlated with the AD experience acquired by petitioning industries in the 1980s and with other policies supporting these industries. In particular, higher numbers of AD petitions may be found in declining industries, which governments tend to protect (e.g. Brainard and Verdier, 1997), and in industries with a higher degree of unionization, which may be more exposed to import competition (Ahlquist and Downey, 2019).

To address these concerns, we construct measures of these potential drivers of $Experience_i$ at the SIC4 level. Industry concentration is captured by two measures: HHI_i, the Herfindahl index of sales concentration, constructed using data from the 1987 Annual Survey of Manufacturers of the U.S. Census Bureau; and EGI_i, the Ellison-Gleaser index of geographical concentration, constructed using 1988 CBP data. To identify declining industries, we construct the variables $Employment\ growth_i$ and $Production\ growth_i$, using data from the NBER-CES database between 1980 and 1987. Finally, $Unionization_i$ measures industry unionization rates and is constructed using data from Pierce and Schott (2016). When we include these variables in the regressions of columns 3-6 of Table A-7, their coefficients are not statistically significant, and the coefficient on $Imports_i^{JP}$ remains positive and significant.[38]

3.2.3 Combining Supply and Demand for Protection

The logic of our identification strategy is that, during a given presidential term, the most protected industries should be those that are more important in battleground states (higher $Swing\ Industry_{i,t}$) and that can exploit this political advantage because of their long-term knowledge of the complex institutional procedures to obtain AD protection (higher $Experience_i$).

Tables A-4 and A-5 in the Appendix provide lists of the top-10 SIC4 industries based on $Swing\ Industry_{i,t}$ and $Experience_i$, with the corresponding level of AD protection. Notice that industries appearing in both lists are protected by higher AD duties relative to industries appearing in only one of the two. For example, sectors "Motor vehicle parts and accessories" (SIC 3714) and "Blast furnaces and steel mills" (SIC 3312) – which are both politically important (respectively ranked 4$^{\text{th}}$ and 7$^{\text{th}}$ based on $Swing\ Industry_{i,t}$) and

[38] In these regressions, we can include HHI_i and EGI_i together, since the correlation between these two measures of industry concentration is very low (0.04). We include separately $Employment\ growth_i$ and $Production\ growth_i$, which are highly correlated (0.57).

both have experience at filing for AD protection (respectively ranked 2[nd] and 1[st] based on $Experience_i$) – receive a high level of protection (the average AD duties on these industries are respectively 142.9% and 81.61%). By contrast, industries like "Search and navigation equipment" (SIC 3812) – which appears in the top-10 list in terms of political importance, but not experience – and "Industrial trucks and tractors" (SIC 3537) – which appears in the top-10 list in terms of experience, but not political importance – receive little or no AD protection.

We thus instrument the variables *Average Input Tariff*$_{j,t}$ and *Tariff on Key Input*$_{j,t}$ defined in (1) and (2) as follows:

$$IV\ Average\ Input\ Tariff_{j,t} = \sum_{i=1}^{N} \omega_{i,j}\ Swing\ Industry_{i,t} \times Experience_i, \tag{7}$$

$$IV\ Tariff\ on\ Key\ Input_{j,t} = Swing\ Industry_{1,j,t} \times Experience_{1,j}. \tag{8}$$

where $\omega_{i,j}$ in (7) denotes the direct requirement coefficient for the sector pair ij and $1, j$ in (8) denotes the most important input in the production of j (with highest $\omega_{i,j}$).

As argued above, the political importance of an industry and its historical experience in the complex US AD institutional procedures are both key determinants of AD duties. Exploiting variation in both supply and demand for protection thus gives us a stronger instrument for trade protection, allowing us to better predict AD duties.

It should be stressed that our identification strategy exploits variation in the political importance of an industry (captured by $Swing\ Industry_{i,t}$) only to the extent that it is relevant for AD protection.[39] This strategy mitigates concerns about the exclusion restriction, since it allows us to isolate the effects of the political importance of an industry on AD duties from the effects on other federal policies (e.g. transfers) that may be used to favor key industries in swing states.

[39]Notice that our instrument predicts no AD protection for industries that are important in swing states (high $Swing\ Industry_{i,t}$) but cannot exploit this political advantage due to their lack of AD experience ($Experience_i = 0$).

4 Effects of Protection on Employment

4.1 Baseline Results

The main goal of our analysis is to identify the impact of input protection on employment in downstream industries. To this purpose, we exploit changes in US tariffs across the seven complete presidential terms covering the 1988-2016 period.

We define the variable $\Delta L_{j,t}$ as the annualized log change in employment in SIC4 industry j during term t.[40] We then estimate the following two-stage least squares (2SLS) specification:

$$\Delta L_{j,t} = \beta_0 + \beta_1 \Delta\tau_{j,t} + \delta_j + \delta_t + \varepsilon_{j,t}, \tag{9}$$

where $\Delta\tau_{j,t}$ is the change in the average input tariff faced by industry j (or in the tariff on the key input of industry j) during term t. This variable is instrumented using the change in $\textit{IV Average Input Tariff}_{j,t}$ as shown in equation (7) (or $\textit{IV Tariff on Key Input}_{j,t}$ as shown in equation (8)). We include sector fixed effects at the SIC4 level (δ_j) to control for trends in downstream industries, as well as term fixed effects (δ_t) to control for variation in macroeconomic and political conditions across terms. We cluster the standard errors at the SIC3 level to allow for correlated industry shocks.

Table 1 reports the results of estimating (9). In columns 1 and 2, we restrict the analysis to manufacturing downstream industries, while in columns 3 and 4 we consider all downstream industries. In all specifications, the estimated coefficient of $\Delta\tau_{j,t}$ is negative and significant, indicating that higher tariffs in upstream industries hamper employment growth in downstream industries.

Comparing across the specifications of Table 1, notice that including all downstream industries helps to identify the negative effects of input protection: in column 1, in which we restrict the analysis to manufacturing downstream industries, the coefficient of $\Delta\tau_{j,t}$ is statistically less significant than the corresponding coefficient in column 3.

The last row of Table 1 reports the Kleibergen-Paap (KP) F-statistics to verify the predictive power of the instrument.[41] These are all well above the critical value of 16.4 based on a 10% maximal IV size, so we can reject the hypothesis that our instrument is weak. In Table A-8 of the Appendix, we show the first-stage results of the 2SLS regressions in Table 1. The coefficient of our instrument is positive and significant at the 1% level in all

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

[41] The KP statistic is a version of the Cragg-Donald statistic adjusted for clustered robust standard errors.

specifications.

Table 1

The impact of tariffs on employment in downstream industries

	Manufacturing sectors		All sectors	
	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input
	(1)	(2)	(3)	(4)
$\Delta\tau_{j,t}$	-0.070*	-0.014***	-0.118***	-0.021***
	(0.041)	(0.005)	(0.044)	(0.005)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,742	2,742	3,351	3,351
KP F-statistic	134.3	1414.2	143.2	2051.6

Notes: The table reports 2SLS estimates. The dependent variable $\Delta L_{j,t}$ is the annualized log change in employment in SIC4 industry j during the term ending in year t. $\Delta\tau_{j,t}$ is the change in the average input tariff of industry j (in columns 1 and 3) or in the tariff on the key input of industry j (in columns 2 and 4). The sample covers 1988-2016. In columns 1 and 2, it comprises only manufacturing sectors, while in columns 3 and 4 it comprises all sectors. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

The baseline estimate reported in column 3 implies that a one percentage point increase in the average input tariff leads to a 0.12 percentage point decrease in the annual growth rate of employment in downstream industries. This is equivalent to a 0.47 percentage point decrease in the growth rate of employment per term. Alternatively, a one standard deviation (0.030) increase in the predicted average input tariff decreases the yearly employment growth by 0.4 percentage points, which explains 23% of the average annual employment growth during 1988-2016. Similarly, column 4 shows that a one standard deviation (0.162) increase in the predicted tariff on the key input slows down the annual growth rate of employment by 0.3 percentage points, explaining 21% of the observed annual growth rate.[42]

We can compare the results of the 2SLS regressions in Table 1 with the corresponding results of OLS regressions. As shown in Table A-9, if we ignore the the endogeneity of trade policy, the estimated coefficient for input protection is negative but not significant in all but one specification. The fact that the negative β_1 coefficient becomes statistically significant (and larger in magnitude) when instrumenting for input tariffs suggests that omitted variables generate a positive bias in the OLS estimates, which makes it harder

[42]These numbers are computed by dividing the predicted change due to a one standard deviation in $\Delta\tau_{j,t}$ by the mean of $\Delta L_{j,t}$ (-0.016).

to identify negative effects of upstream protection on employment growth in downstream industries.

To quantify the number of jobs lost due to input protection, we apply the methodology proposed by Acemoglu *et al.* (2016) and perform the following counterfactual exercise:

$$\textit{Employment Losses} = \sum_{j,t} L_{j,t}(1 - e^{-\hat{\beta}_1 \Delta\widetilde{\tau}_{j,t}}), \tag{10}$$

where $L_{j,t}$ is the employment level in industry j at the end of term t, $\hat{\beta}_1$ is the estimated coefficient of $\Delta\tau_{j,t}$ in the second stage, and $\Delta\widetilde{\tau}_{j,t}$ is the actual change in the average input tariff, weighted by the partial R^2 in the first stage.

If we use the baseline estimates in column 3 of Table 1 to carry out this counterfactual exercise, we find that around 570,000 US jobs were lost across all downstream industries due to input protection.[43] The effects are smaller (almost 110,000 jobs lost) if we use the estimates in column 1 of Table 1, which restricts the analysis to manufacturing downstream industries.

Table A-10 in the Appendix lists the ten downstream industries most negatively affected by input protection. These include large non-manufacturing industries, which have suffered from high tariffs on their manufacturing inputs. For example, during the 1988-2016 period, SIC 1510 ("Construction") faced an average input tariff of 9.96% and an average tariff on its key input, SIC 3312 ("Blast furnaces and steel mills") of 81.61%. Our estimates imply that average input protection accounts for around 51,000 US jobs lost in the construction industry during this period. Thus protecting jobs in manufacturing sectors can have large negative employment effects of non-manufacturing sectors that rely on the protected inputs.

It is interesting to compare our baseline results with Trimarchi's (2020). His estimates for the 1988-2016 period suggest that US AD duties against China saved around 22,000 jobs in the protected industries. Our estimates show that these are less than 5% of the jobs destroyed by the same tariffs in the rest of the economy, when considering the effects along value chains.

Our counterfactual results are likely to be an underestimate of the actual cost of protection, since we do not take into account that increasing tariffs in some sectors can hurt producers in other sectors through general equilibrium effects. The fact that net job losses from trade protection are negative (when accounting for the effects on both protected and downstream industries) implies additional job losses in other sectors through a fall in de-

[43] The partial R^2 in the first stage is 0.094.

mand for goods and services, as shown by the literature on multipliers (e.g. Moretti, 2010; Moretti and Wilson, 2014).[44]

4.2 Robustness Checks

The main result of our analysis is that increases in input tariffs lead to a significant decline in the growth rate of employment in downstream industries. We have carried out a series of additional estimations that we have carried out to verify the robustness of this finding. The results can be found in the Appendix. In the interest of space, we focus on the baseline specifications corresponding to columns 3 and 4 of Table 1, omitting the specifications that restrict the analysis to manufacturing sectors.

First, in Table A-11 we verify that the results are robust to using alternative AD measures. The variables *Average Input Tariff*$_{j,t}$ and *Tariff on Key Input*$_{j,t}$ captures mostly variation in the intensive margin of protection. However, there is also considerable cross-industry variation in the extensive margin of AD protection. In Table A-11, we use the three alternative protectionist measures described in Section 2, which capture variation on the extensive margin of input protection. Notice that the coefficient of $\Delta\tau_{j,t}$ remains negative and significant at the 1% level across all eight specifications.

In Table A-12, we verify that the negative effects of upstream protection on downstream employment are robust to controlling for the change in US applied MFN tariffs (columns 1 and 2),[45] accounting for other TTBs (countervailing duties and safeguards) applied by the US against China (columns 3 and 4),[46] and for AD duties applied to non-manufacturing inputs (columns 5 and 6). Once again, the coefficient of $\Delta\tau_{j,t}$ is negative and significant in all specifications.

In Table A-13, we consider alternative econometric methodologies and show that the results continue to hold if we change our dependent variable to yearly differences instead of term differences (columns 1 and 2), use broader industry clusters at the SIC2 level (columns 3 and 4) or narrower clusters at the SIC4 level (columns 5 and 6).

[44]Moretti (2010) finds that for each additional job in a manufacturing tradable sector in a given city, 1.6 jobs are created in non-tradable sectors in the same city. This multiplier is found to be significantly larger (around 5) when focusing on job creation in manufacturing sectors that are more innovative, such as the high-tech sector. Moretti and Wilson (2014) find a large local job multiplier, especially for construction and retail, from job creation in biotech companies in the US.

[45]The coefficient of the MFN variable (not reported) is not insignificant. This is not surprising, since US MFN rates vary little over time, as mentioned in Section 2.

[46]Countervailing duties on China are almost always applied in combination with antidumping duties. When the measures are combined, we compute the average input tariff using the duty determined jointly from the antidumping and countervailing investigations.

Finally, in Table A-14, we use alternative methodologies to identify vertically-related industries. In our benchmark regressions, we use direct requirement coefficients to construct our input protection variables and focus on the effects of AD duties applied to all manufacturing input sectors different from j. The results reported in columns 1 and 2 show that our results are robust to using total requirement coefficients to construct the measures of input protection, thus allowing for both direct and indirect vertical linkages. The estimates in columns 3 and 4 show that the results are also unaffected if we include the diagonal of the input-output matrix (i.e. $\omega_{j,j}$) when constructing these measures.

4.3 Extending the Analysis to the Trump Era

In our analysis so far, we have focused on the effects of US AD duties against China during the seven complete presidential terms covering the 1988-2016 period. As mentioned in Section 2, since President Trump took office in January 2017, China has been the target of even higher AD protection. Moreover, Trump introduced additional tariffs, which were stacked on top of existing AD duties.

Since the CBP data on industry-level employment is only available until 2018, in Table 2, we extend our analysis to protectionist measures introduced during the first two years of Trump's presidency. In columns 1-2, we reproduce the main specifications of Table 1, including the AD duties introduced during 2017-2018, while in columns 3-4 we include all TTBs (AD, CVDs, safeguards) applied against China since 1988, as well as the additional tariffs introduced during Trump's presidency.

The coefficient of $\Delta\tau_{j,t}$ in column 3 implies that a one standard deviation (0.042) increase in the average input tariff leads to a 0.5 percentage point decrease in the growth rate of employment in downstream industries. Using this estimate to carry out the counterfactual exercise in equation (10), we find that around 185,000 US jobs were lost across downstream industries due to protectionist measures introduced during the first two years of Trump's presidency.

Recall that the baseline estimates of Table 1 imply that during the 1988-2016 period around 570,000 US jobs were lost in downstream industries due to AD protection in upstream industries, i.e. an average of around 81,500 jobs lost in each of the seven complete presidential terms. The results of Table 2 indicate that the AD duties and other protectionist measures introduced during the first two years of Trump's presidency caused much larger losses along supply chains.

Table 2

The impact of tariffs on employment in downstream industries (1988-2018)

	AD only		All TTBs + Trump's tariffs	
	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input
	(1)	(2)	(3)	(4)
$\Delta\tau_{j,t}$	-0.093**	-0.016***	-0.118**	-0.019***
	(0.040)	(0.005)	(0.051)	(0.006)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,829	3,829	3,829	3,829
KP F-statistic	165.3	1,335.7	142.9	950.1

Notes: The table reports 2SLS estimates. The dependent variable $\Delta L_{j,t}$ is the annualized log change in employment in SIC4 industry j during the term ending in year t. $\Delta\tau_{j,t}$ is the change in the average input tariff of industry j (in columns 1 and 3) or in the tariff on the key input of industry j (in columns 2 and 4); the variable is constructed based only AD duties against China (columns 1-2) or including all TTBs and other protectionist measures against China (columns 3-4). The sample covers 1988-2018. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

4.4 Placebo Tests

Our identification strategy exploits exogenous variation in the political importance of US states across presidential terms. The variable $Swing_{s,t}$ identifies states to be electorally competitive based on the difference in the vote shares of the Democratic and Republican candidates in the previous presidential election. Figure 2 illustrates which states were classified as swing in each presidential term since 1988.

Although the political treatment variable is defined at the state-term level, our instrument predicts that its effect on trade protection should vary across industries: in electoral terms in which some states are classified as swing, industries that are more important in these states should get more protection, particularly if they have prior knowledge of the complex legal and institutional AD procedures.

To verify the logic behind of our identification strategy, we carry out a placebo test, using a randomized distribution of swing states to construct the political treatment variable. Within each presidential term, we randomly choose the swing states across all the 50 US states.[47] We perform 1,000 randomizations.[48] From each randomization, we obtain a variable $Placebo\ Swing_{s,t}$. Using this variable, we construct a placebo instrument, which we use in our first-stage regressions to predict changes in AD protection.[49]

The top panel of Figure A-7 in the Appendix shows the distribution of the 1,000 coefficients of the first-stage regressions. The mean of the distribution is 0 and not statistically significant. On average, we thus cannot predict AD protection based on a randomized distribution of swing states. This can also be seen from the bottom panel of Figure A-7, in which we plot the 1,000 coefficients with their 99% confidence intervals. The red cross in this panel corresponds to the estimated coefficient in our baseline first-stage regression (column 3 of Table A-8), which is positive and significant at the 1% level. Overall, Figure A-7 shows that the actual identity of swing states matters for predicting AD protection.

In an alternative placebo test, we randomize across those states that were classified as swing at least once during the last eight presidential terms. Again, the mean of the distribution of the 1,000 first-stage coefficients is 0 and not statistically significant. This exercise shows that predicting AD protection requires a time-varying instrument, which keeps track of changes in the identity of swing states across terms.

5 Effects of Protection on Input Prices

In our analysis so far, we have shown that AD duties have negative effects along supply chains, reducing their growth rate of employment in downstream industries. In what follows, we provide evidence for the mechanism behind this result: higher tariffs increase the prices of imported and domestically produced inputs, raising the cost of production in downstream industries.

To this purpose, we run 2SLS term regressions similar to equation (9), examining the impact of tariff changes on changes in the prices of imported and domestically produced inputs. The dependent variable is $\Delta Input\ Prices_{j,t}$, the annualized log growth rate of average input prices faced by producers in industry j during term t. This variable is constructed using (3) for imported inputs and (4) for domestically produced inputs.

The results are reported in Table 3. In columns 1 and 2, we examine the effects of AD duties against China on the price of inputs imported from China. As mentioned in Section

[47] The number of swing states in a given term is kept as in Figure 2. For example, we randomly choose six states for the presidential term 2008-2012 and four states for 2012-2016.

[48] Each randomization consists of independent random draws of swing states, one per presidential term.

[49] The placebo IV variable is constructed by replacing the dummy variable $Swing_{s,t}$ with $Placebo\ Swing_{s,t}$ in equations (5) and (7).

2.4, for each industry j, we have combined data from Comtrade on unit values of US imports with input-output data from the BEA to construct a measure of the average price of inputs imported from China. The coefficient of $\Delta\tau_{j,t}$ is positive and significant, indicating that input tariffs raise the price of inputs charged by foreign producers.

Table 3
The impact of tariffs on input prices

	Prices of imported inputs		Prices of domestic inputs	
	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input
	(1)	(2)	(3)	(4)
$\Delta\tau_{j,t}$	0.133***	0.019***	0.082***	0.005*
	(0.044)	(0.006)	(0.015)	(0.003)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,872	2,872	3,351	3,351
KP F-statistic	153.6	2,300.2	143.2	2,051.6

Notes: The table reports 2SLS estimates. The dependent variable $\Delta Input\ Prices_{j,t}$ is the annualized log change in input prices faced by SIC4 industry j during the term ending in year t. In columns 1-2, this variable is constructed using data on unit values of US imports from China, while in columns 3-4 it is constructed based on US PPI data. $\Delta\tau_{j,t}$ is the change in the average input tariff of industry j (in columns 1 and 3) or in the tariff on the key input of industry j (in columns 2 and 4). The sample covers 1988-2016. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

The estimates in column 1 imply that a one standard deviation (0.033) increase in the predicted average input tariff increases the annual growth rate of import prices by 0.44 percentage points, which explains 37% of the average annual growth rate of the price of imported inputs during 1988-2016. Similarly, column 2 shows that a one standard deviation (0.193) increase in the predicted tariff on the key input increases the annual growth rate of imported input prices by 0.36 percentage points, explaining 30% of the observed annual price growth.[50] These results are consistent with the findings of recent studies on the US-China trade war discussed in Section 1. Amiti *et al.* (2019b), Cavallo *et al.* (2019), and Fajgelbaum *et al.*, (2020) find complete pass-through of Trump's tariffs into domestic prices of imported goods. Our findings are also in line with the literature on pass-through of AD, which shows

[50] These numbers are computed by dividing the predicted change due to a one standard deviation in $\Delta\tau_{j,t}$ by the mean of the dependent variable (0.012).

that exporters increase their prices in response to higher duties (e.g. Blonigen and Park, 2004; Blonigen and Haynes, 2002 and 2010; Lu *et al*, 2013).[51]

In columns 3 and 4, we examine instead the impact of AD duties against China on domestic input prices, using PPI data from the BLS.[52] Again, the coefficient of $\Delta\tau_{j,t}$ is positive and significant, indicating that higher input tariffs raise the price of inputs charged by domestic producers. Column 3 indicates that a one percentage point increase in the average input tariff leads to an increase in the growth rate of domestic input prices by 0.08 percentage points each year (equivalent to an increase of 0.3 percentage points over the term). Alternatively, a one standard deviation (0.030) increase in the predicted average input tariff increases the annual growth rate of domestic input prices by 0.3 percentage points, which explains 13% of the average annual growth rate of domestic input prices during 1988-2016. Similarly, column 4 shows that a one standard deviation (0.162) increase in the predicted tariff on the key input causes domestic prices to grow faster by 0.1 percentage points, explaining about 4% of the observed annual growth rate in US prices.[53] These results are in line with the findings of effects of the US-China trade war. Using PPI data, Amiti *et al.* (2019b) show that Trump's tariffs have increased the prices charged by domestic producers.[54] Similarly, Flaaen and Pierce (2019) find that the tariff hikes enacted in 2018 by the Trump administration are associated with increases in US producer prices.

Overall, the results of Table 3 indicate that AD duties increase the price of both imported and domestically produced inputs. Thus higher tariffs in upstream industries increase production costs for firms in downstream industries, independently of whether they source the protected inputs from foreign or domestic suppliers.

[51]Our estimates imply smaller effects of AD duties on export prices when compared to the existing literature. This can partly be due to the fact that we study these effects i) at a more aggregate level (industry, rather than product), which can give rise to measurement error, and ii) over a longer period (4-year terms, rather than years or months), allowing more time for markup adjustments.

[52]Notice that the number of observations is larger than in columns 1-2. This is because the import data from Comtrade is only available from 1991, so the sample excludes the 1988-1992 presidential term.

[53]These numbers are computed by dividing the predicted change due to a one standard deviation in $\Delta\tau_{j,t}$ by the mean of the dependent variable (0.019).

[54]Amiti *et al.* (2019a) show that the extent to which firms respond to international cost shocks depends on their market power and on strategic complementaries between them. Small firms exhibit no strategic complementarities in price setting and complete cost pass-through. By contrast, large firms exhibit strong strategic complementarities, adjusting their markups in response to both competitor price changes and their own cost shocks with roughly equal elasticities of around 0.5.

6 Effects of Protection on Other Outcome Variables

We next study the effects on other industry outcomes, using data from the NBER-CES Manufacturing Industry Database. A drawback of using this dataset is that it only provides information for manufacturing industries, and only 2011. This significantly reduces the sample size and does not allow us to examine the effects on non-manufacturing downstream industries.

Table 4

The impact of tariffs on other industry outcomes

	Blue Collar		White Collar	
	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input
	(1)	(2)	(3)	(4)
$\Delta\tau_{j,t}$	-0.154**	-0.028***	-0.116*	-0.019**
	(0.069)	(0.006)	(0.063)	(0.008)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,320	2,320	2,320	2,320
KP F-statistic	119.0	1,842.7	119.0	1,842.7
	Sales		Investment	
	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input
	(1)	(2)	(3)	(4)
$\Delta\tau_{j,t}$	-0.133*	-0.024***	-0.117	-0.035**
	(0.073)	(0.009)	(0.119)	(0.017)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,320	2,320	2,320	2,320
KP F-statistic	119.0	1,842.7	119.0	1,842.7

Notes: The table reports 2SLS estimates. The dependent variable is the annualized log change in the number of blue-collar and white-collar jobs (top panel) and in sales and investment (bottom panel) in SIC4 industry j during the term ending in year t. $\Delta\tau_{j,t}$ is the change in the average input tariff of industry j (in columns 1 and 3) or in the tariff on the key input of industry j (in columns 2 and 4). The sample covers 1988-2011 and includes only manufacturing downstream sectors. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

We first estimate 2SLS regressions to examine the impact of input protection on blue- and white-collar jobs. The results are reported in the top panel of Table 4. Notice that the number of observations in Table 4 is much smaller than in our baseline specification in column 3 of Table 1 (2,320 instead of 3,351), due to the restricted sector and time coverage of the NBER-CES dataset. Still, the coefficient of $\Delta\tau_{j,t}$ is negative and significant in all specifications, indicating that higher tariffs in upstream sectors reduce the growth rate of both blue- and white-collar jobs in downstream manufacturing sectors.

We next estimate 2SLS regressions to examine the impact of input protection on sales and investment in downstream sectors. The results are reported in the bottom panel of Table 4. The coefficient of $\Delta\tau_{j,t}$ is negative and significant in three of the four specifications, indicating that higher tariffs in upstream sectors reduce sales growth and hamper investment growth in downstream sectors.

In Table 4 we use the same instrument to study the effects of trade protection on different outcome variables. 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 four outcome variables jointly, and applying the Romano-Wolf correction with 1,000 bootstrapped replications, we find that even though the p-values of our benchmark coefficients rise slightly, the significance levels remain the same as in Table 4.[55]

7 Conclusions

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 have shown that, well before Trump took office, the US had been applying increasingly high tariffs on imports from China, in the form of AD duties. Combining detailed information on these measures with US input-output data, we have examined the effects of protection along supply chains.

Our analysis emphasizes the importance of addressing concerns about the endogeneity of trade policy for identifying the impact of tariffs along supply chains. We show that, if we ignore these concerns and estimate simple OLS regressions, we find no evidence that higher tariffs in upstream industries affect downstream industries. If instead we instrument for AD tariffs – exploiting exogenous variation in the political importance of different industries and their ability to petition for AD – we find that they lead to a significant decrease in

[55] The results of Tables 1 and 3 are also robust to the Romano-Wolf correction when considering the three outcome variables (employment, prices of imported inputs, prices of domestic inputs) jointly for the 1988-2016 period. These results are available upon request.

employment in downstream industries, affecting both blue-collar and while-collar jobs. Sales and investment are also negatively affected. We further show that the negative effects of tariffs along supply chains work through their impact on input prices.

Our baseline estimates imply that, between the start of the presidency of George H. W. Bush in 1988 and the end of Barack Obama's second term in 2016, input protection destroyed 570,000 US jobs in downstream industries. The effects are smaller (around 110,000 jobs lost) if we restrict the analysis to manufacturing downstream industries. Our results suggest that the negative employment effects of protection along value chains are much larger than the positive employment effects experienced by protected industries (a gain of around 22,000 jobs) documented by Trimarchi (2020).

Our analysis also reveals that President Trump made things worse for downstream producers: our estimates imply that almost 200,000 US jobs were lost across all downstream industries due to protectionist measures introduced during the first two years of his term.

Our results resonate with arguments often heard in the media concerning the costs of protection along supply chains. For example, in a joint statement in March 2018, the National Tooling and Machining Association and the Precision Metalforming Association raised concerns about the damages inflicted on them by Trump's tariffs on steel and aluminum. The statement emphasizes 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, suggesting that the costs of protection for downstream industries are likely to outweigh the benefits for protected industries.[56]

[56] "Thousands of jobs at risk over tariffs, US manufacturers warn" (*Financial Times*, March 1, 2018).

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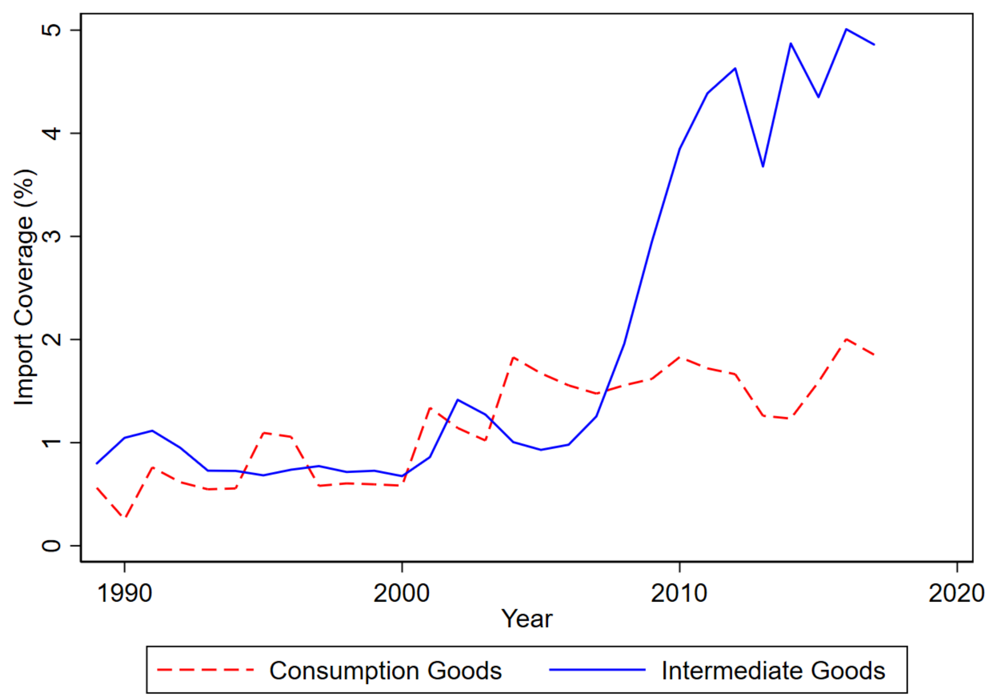
Appendix

A-1 Figures

Figure A-1

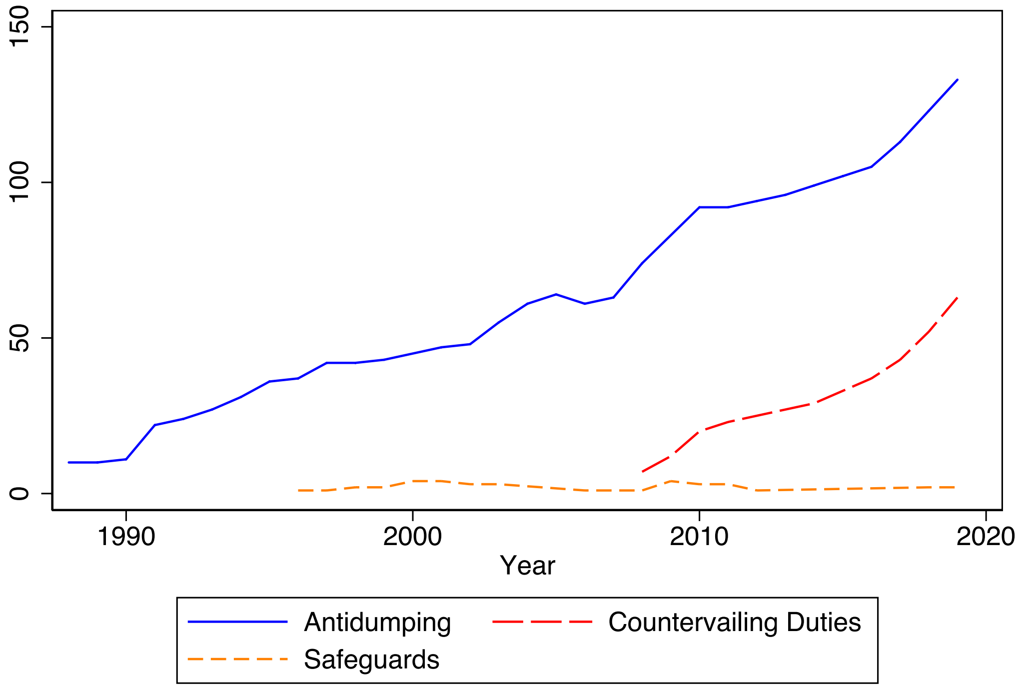
Share of US imports from China covered by temporary trade barriers



Notes: The figure plots the share of US imports from China covered by antidumping duties, countervailing duties, and safeguards applied by the United States on imports from China. Imports are divided into consumption and intermediate goods based on the Broad Economic Categories (BEC) classification of the United Nations. Source: Bown (2019).

Figure A-2

Number of US AD duties, countervailing duties, and safeguards against China (1988-2019)

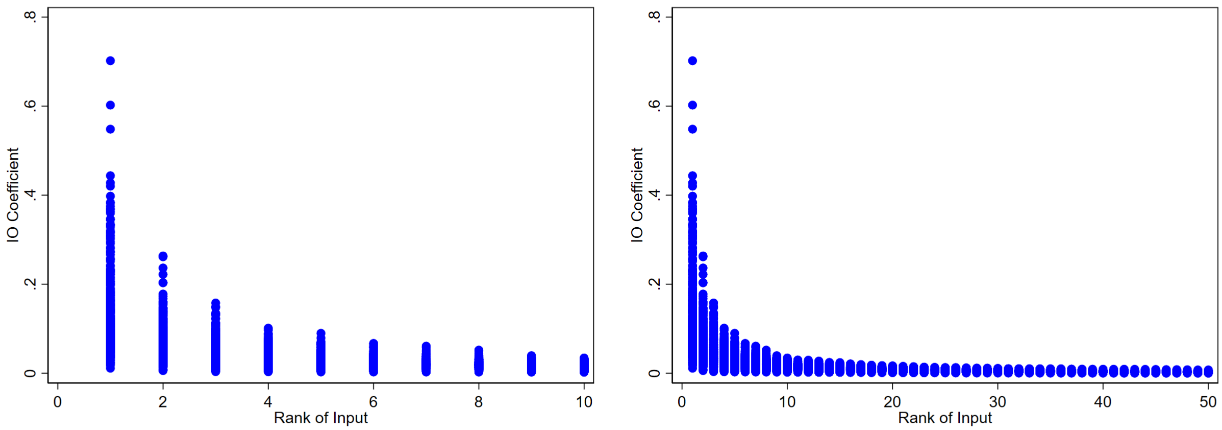


Notes: The figure plots the number of AD duties, countervailing duties, and safeguards applied by the US on imports from China. Source: Authors' calculations bases on an extended version of the Temporary Trade Barriers Database.

Figure A-3

Average IO coefficients of the most important inputs

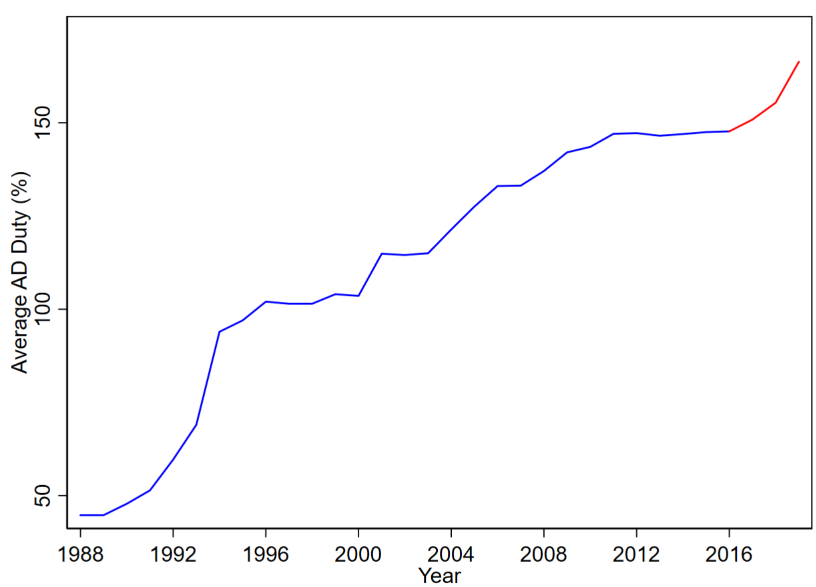
(a) Top-10 (b) Top-50



Notes: The figures plot the average direct requirement coefficients $\omega_{i,j}$ across all 479 SIC4 j industries, focusing on the top-10 and top-50 most important inputs $i(\neq j)$ for each industry j (i.e. highest $\omega_{i,j}$) in panels (a) and (b) respectively.

Figure A-4

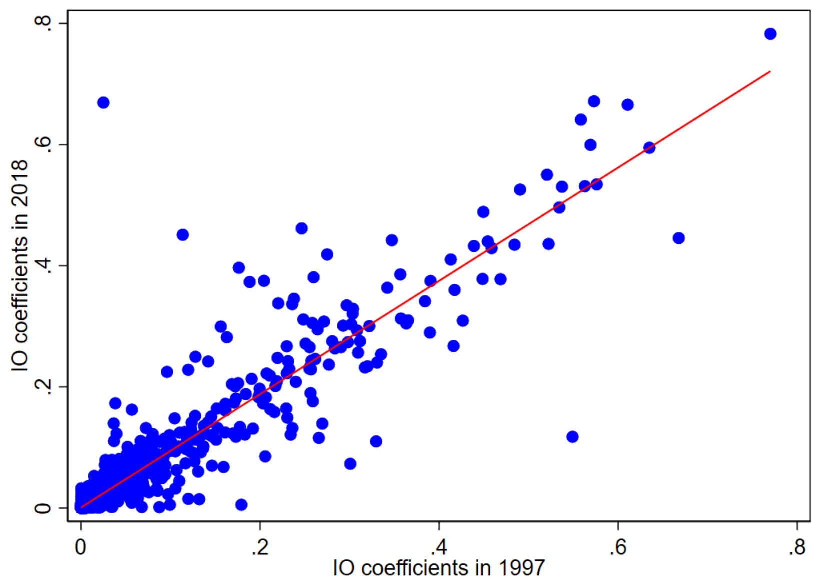
Average AD duty against China (1988-2019)



Notes: The figure plots the average AD duty applied by the US on imports from China. The red part corresponds to Trump's presidency (2017-2019). Source: Authors' calculations based on an extended version of the Temporary Trade Barriers Database.

Figure A-5

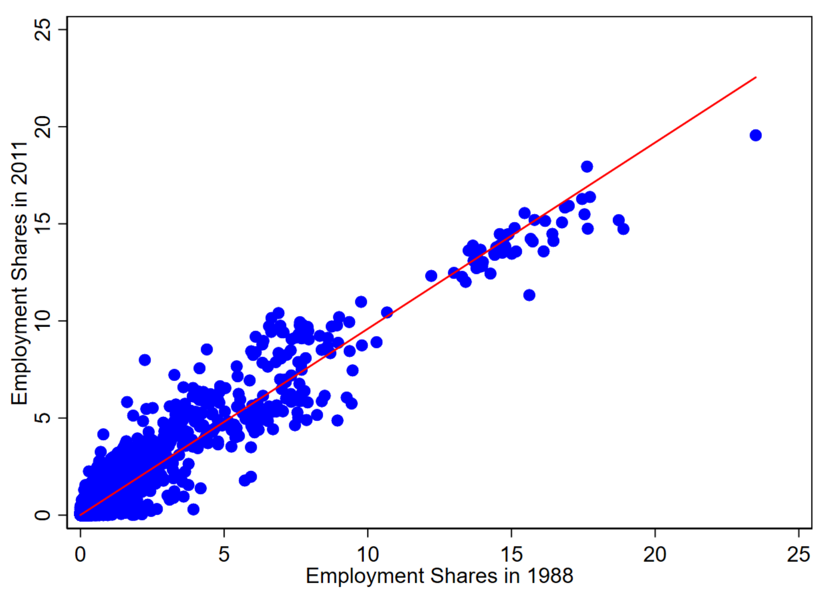
IO coefficients



Notes: The figure plots direct requirement coefficients from the BEA 1997-2018 tables. Industry classifications are concorded over time and aggregated to 71 industries.

Figure A-6

SIC4 employment shares by state

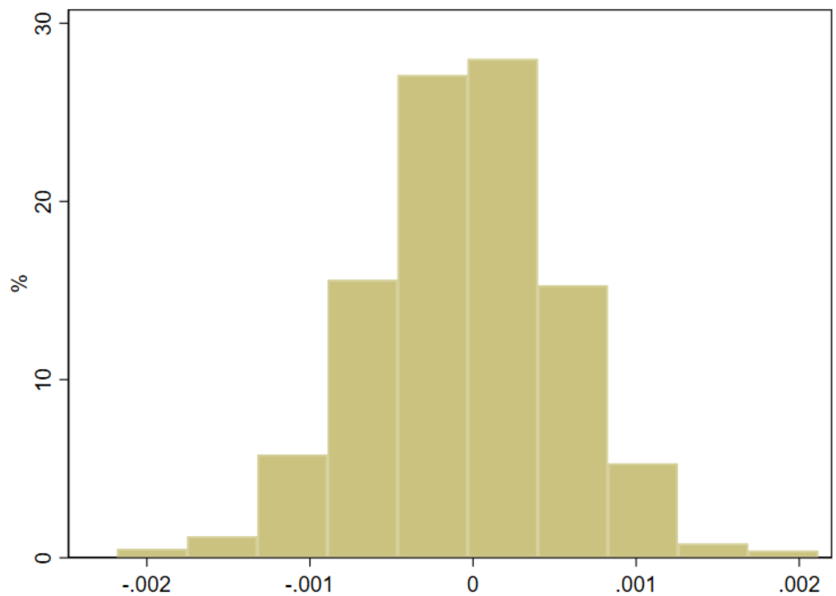


Notes: The figure plots state-level industry employment shares in 1988 and 2011, based on data from Acemoglu *et al.* (2016).

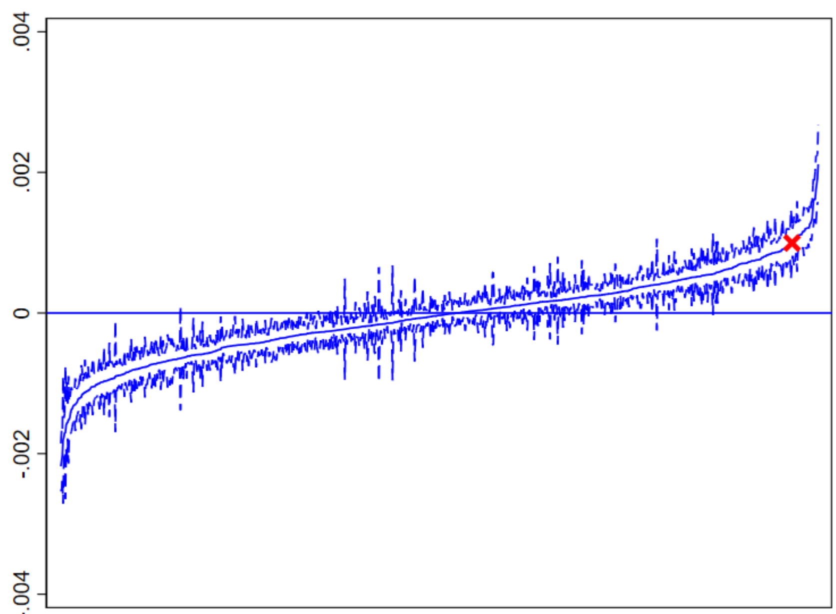
Figure A-7

Coefficients of first-stage regressions,
based on 1,000 randomizations of the swing states

(a) Histogram



(b) Coefficients



Notes: Panel (a) plots the distribution of the estimated first-stage coefficients using our placebo IVs, based on 1000 randomizations of the swing states. In each randomization, the swing states in a presidential term are randomly chosen out of the 50 states. Panel (b) shows the 1,000 estimated first-stage coefficients (with 99% confidence intervals). The red cross corresponds to the estimated coefficient in our baseline first-stage regression (column 3 of Table A-8).

A-2 Descriptive Statistics

Table A-1

Descriptive statistics on AD duties applied by the United States against China

		1988-2016		
Variable	Mean	Std. Dev.	Min	Max
Tariff ($\tau_{i,t}$)	0.15	0.51	0.00	4.30
Average Input Tariff ($\tau_{j,t}$)	0.14	0.15	0.00	1.06
Tariff on Key Input ($\tau_{1,j,t}$)	0.39	0.64	0.00	2.50
		2017-2018		
Variable	Mean	Std. Dev.	Min	Max
Tariff (τ_{it})	0.36	0.81	0.00	4.93
Average Input Tariff ($\tau_{j,t}$)	0.33	0.21	0.02	1.01
Tariff on Key Input ($\tau_{1,j,t}$)	0.97	0.91	0.00	4.93

Notes: The table reports descriptive statistics on US AD duties applied to imports from China during the last seven complete presidencies (top panel) and during Trump's presidency (bottom panel). The rates reported are ad valorem. The variable τ_{it} is constructed for the 392 manufacturing sectors only, while the variable τ_{jt} can be constructed for all 479 industries.

Table A-2

Descriptive statistics on MFN tariffs and Trump's tariffs

		MFN, 1988-2016		
Variable	Mean	Std. Dev.	Min	Max
Tariff ($\tau_{i,t}$)	0.05	0.21	0.00	3.50
Average Input Tariff ($\tau_{j,t}$)	0.02	0.03	0.00	0.43
Tariff on Key Input ($\tau_{1,j,t}$)	0.05	0.23	0.00	3.50
		Trump's additional tariffs, 2018		
Variable	Mean	Std. Dev.	Min	Max
Tariff (τ_{it})	0.11	0.07	0.00	0.25
Average Input Tariff ($\tau_{j,t}$)	0.05	0.03	0.00	0.13
Tariff on Key Input ($\tau_{1,j,t}$)	0.13	0.05	0.00	0.25

Notes: The table reports descriptive statistics on MFN tariffs applied by the United States during 1988-2016 and Section 201, 232, and 301 tariffs applied during Trump's presidency by the end of 2019 (bottom panel). The rates reported are ad valorem. The variable τ_{it} is constructed for the 392 manufacturing sectors only, while the variable τ_{jt} is constructed for all 479 industries.

Table A-3

Top 10 key inputs

SIC4	Input industry	Share of downstream industries (1)	Average cost share of key input (2)
3312	Blast furnaces and steel mills	0.18	0.11
2911	Petroleum refining	0.09	0.05
2752	Commercial printing, lithographic	0.06	0.03
2221	Broadwoven fabric mills, manmade	0.06	0.10
2869	Industrial organic chemicals, n.e.c.	0.05	0.09
2621	Paper mills	0.05	0.20
3679	Electronic components, n.e.c.	0.05	0.06
3089	Plastics products, n.e.c.	0.03	0.04
2421	Sawmills and planing mills, general	0.03	0.20
2821	Plastics materials and resins	0.03	0.12

Notes: The table list the 10 most important manufacturing input industries i. Column (1) reports the share 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 downstream industries j for which i is the key input).

Table A-4

$Swing\ Industry_{i,t}$ - Top-10 Sectors

Sector	Description	$Swing\ Industry_{i,t}$	$Experience_i$	$Tariff_{i,t}$ (%)
2752	Commercial printing, lithographic	0.030	1	35.78
3089	Plastics products, n.e.c.	0.028	3	1.461
2599	Furniture and fixtures, n.e.c.	0.024	3	71.06
3714	Motor vehicle parts and accessories	0.023	8	80.88
2711	Newspapers	0.022	0	0
3711	Motor vehicles and car bodies	0.017	2	0
3312	Blast furnaces and steel mills	0.016	57	81.61
3812	Search and navigation equipment	0.015	0	0
3499	Fabricated metal products, n.e.c.	0.014	1	70.66
3599	Industrial machinery, n.e.c.	0.013	1	106.6

Notes: The table presents the descriptive statistics of the top-10 SIC4 sectors with the highest average value of $Swing\ Industry_{i,t}$ during 1988-2016.

Table A-5

$Experience_i$ - Top-10 Sectors

Sector	Description	$Swing\ Industry_{i,t}$	$Experience_i$	$Tariff_{i,t}$ (%)
3312	Blast furnaces and steel mills	0.016	57	81.61
3714	Motor vehicle parts and accessories	0.023	8	142.9
2869	Industrial organic chemicals, n.e.c.	0.005	6	125.1
3496	Misc. fabricated wire products	0.003	6	114.7
2819	Industrial inorganic chemicals, n.e.c.	0.004	5	69.94
2241	Narrow fabric mills	0.001	5	59.78
3537	Industrial trucks and tractors	0.002	4	0.970
2399	Fabricated textile products, n.e.c.	0.002	4	30.74
3991	Brooms and brushes	0.001	4	98.24
3069	Fabricated rubber products, n.e.c.	0.007	4	0

Notes: The table presents the descriptive statistics of the top-10 SIC4 sectors with the highest average value of $Experience_i$ defined between 1980-1987.

Table A-6

Top-10 protected sectors, by average input tariff

SIC4	SIC4 description	Average input tariff	Average tariff on key input	Key input SIC4	Key input description
3449	Miscellaneous metal work	49.98%	81.61%	3312	Blast furnaces and steel mills
2653	Corrugated and solid fiber boxes	43.79%	76.93%	2621	Paper mills
3412	Metal barrels, drums, and pails	43.64%	81.61%	3312	Blast furnaces and steel mills
3448	Prefabricated metal buildings	42.96%	81.61%	3312	Blast furnaces and steel mills
2821	Plastics materials and resins	42.16%	125.09%	2869	Industrial organic chemicals, n.e.c.
2674	Bags: uncoated paper and multiwall	40.57%	76.93%	2621	Paper mills
3084	Plastics pipe	40.53%	53.04%	2821	Plastics materials and resins
2655	Fiber cans, drums and similar products	39.58%	76.93%	2621	Paper mills
3465	Automotive stampings	39.05%	81.61%	3312	Blast furnaces and steel mills
2851	Paints and allied products	38.67%	125.09%	2869	Industrial organic chemicals, n.e.c.

Notes: Column 1 shows the top-10 SIC4 downstream sectors that face the highest average input tariffs, based on US AD duties, and column 2 indicates the SIC4 description. Column 3 (column 4) shows the average input tariff (average tariff on the key input sector) over 1988-2016. The SIC code and description of the key input are identified in columns 5 and 6, respectively.

A-3 Additional Results

Table A-7

Determinants of AD experience

	(1)	(2)	(3)	(4)	(5)	(6)
Imports_i^{JP}	0.22**	0.31**	0.24**	0.31**	0.25**	0.32**
	(0.09)	(0.14)	(0.09)	(0.13)	(0.10)	(0.14)
HHI_i			-0.00	-0.00	-0.00	-0.00
			(0.00)	(0.00)	(0.00)	(0.00)
EGI_i			3.25	1.23	3.24	1.35
			(2.45)	(2.61)	(2.43)	(2.28)
Unionization_i			0.05	0.05	0.05	0.05
			(0.04)	(0.04)	(0.04)	(0.04)
$\text{Employment growth}_i$			-0.00	-0.00		
			(0.01)	(0.01)		
$\text{Production growth}_i$					-0.00	-0.00
					(0.00)	(0.00)
Industry FE	No	Yes	No	Yes	No	Yes
Observations	391	391	370	370	370	370
Adj-R^2	0.04	0.05	0.06	0.06	0.06	0.06

Notes: The table reports OLS estimates. The dependent variable is $Experience_i$, the number of AD petitions filed by SIC4 industry i during the 1980-1987 period. $Imports_i^{JP}$ is the log of average US imports from Japan during 1980-1987. HHI_i is the Herfindahl index of sales concentration in 1987, while EGI_i is the Ellison-Gleaser index of geographical concentration in 1988. $Unionization_i$ is the industry's unionization rate in 1987. $Employment\ growth_i$ and $Production\ growth_i$ are the growth rates of employment and production in 1980-1987. The industry fixed effects correspond to the 10 broad manufacturing industries defined in Acemoglu *et al.* (2016). Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-8

First-stage results for Table 1

	Manufacturing sectors		All sectors	
	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input
	(1)	(2)	(3)	(4)
$\Delta IV_{j,t}$	0.001***	0.723***	0.001***	0.718***
	(0.000)	(0.019)	(0.000)	(0.016)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,742	2,742	3,351	3,351
Adj-R^2	0.26	0.21	0.25	0.19
KP F-statistic	134.3	1,414.2	143.2	2,051.6

Notes: The table reports the first-stage results of the 2SLS estimates reported in Table 1. The dependent variable $\Delta\tau_{j,t}$ is the change in the average input tariff faced by industry j (in columns 1 and 3) or in the tariff on the key input of industry j (in columns 2 and 4). The sample covers 1988-2016. In columns 1 and 2, it comprises only manufacturing downstream sectors, while in columns 3 and 4 it comprises all sectors. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-9

Tariffs and employment in downstream industries (OLS)

	Manufacturing sectors		All sectors	
	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input
	(1)	(2)	(3)	(4)
$\Delta\tau_{j,t}$	-0.016	-0.001	-0.025*	-0.002
	(0.013)	(0.003)	(0.013)	(0.002)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,742	2,742	3,351	3,351
Adjusted R^2	0.35	0.35	0.37	0.37

Notes: The table reports OLS estimates. The dependent variable $\Delta L_{j,t}$ is the annualized log change in employment in SIC4 industry j during the term ending in year t. $\Delta\tau_{j,t}$ is the change in the average input tariff of industry j (in columns 1 and 3) or in the tariff on the key input of industry j (in columns 2 and 4). The sample covers 1988-2016. In columns 1 and 2, it comprises only manufacturing downstream sectors, while in columns 3 and 4 it comprises all sectors. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-10

Top-10 downstream sectors, by number of jobs lost due to input protection

SIC4	SIC4 description	Share of total US employment	Average input tariff	Employment loss due to average input tariffs
5812	Eating and drinking places	7.94%	10.61%	-62,912
1510	Construction	5.47%	9.96%	-51,188
5210	Retail trade	13.25%	3.19%	-44,611
5012	Wholesale trade	6.11%	4.01%	-27,466
8060	Hospitals	4.90%	5.97%	-20,586
7532	Auto repair	0.67%	20.16%	-13,478
8320	Social services	1.14%	6.67%	-10,102
2752	Commercial printing, lithographic	0.49%	21.69%	-9,736
7371	Computer services	1.60%	3.38%	-8,805
4210	Trucking	1.71%	4.56%	-7,925

Notes: The table lists the ten SIC4 sectors that suffered the largest predicted job losses due to input protection during 1988-2016. Columns 1 and 2 list the SIC codes of these sectors and the corresponding description. Column 3 reports the sector's average share in total US employment, and column 4 indicates the average input tariff faced by the sector. Column 5 reports the predicted number of job losses, derived by applying our baseline result in column 3 of Table 1 to equation (10).

A-4 Robustness Checks

Table A-11

The impact of tariffs on downstream industries
(alternative AD measures)

	Dummy		Count of products		Import coverage	
	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\tau_{j,t}$	-0.159***	-0.028***	-0.027***	-0.005***	-4.857***	-0.959***
	(0.060)	(0.007)	(0.010)	(0.001)	(1.823)	(0.244)
SIC4 FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,351	3,351	3,351	3,351	3,351	3,351
KP F-statistic	141.4	3,091.0	162.8	8,592.1	111.2	559.2

Notes: The table reports 2SLS estimates. The dependent variable $\Delta L_{j,t}$ is the annualized log change in employment in SIC4 industry j during the term ending in year t. $\Delta\tau_{j,t}$ is the change in the average input tariff of industry j (in columns 1, 3 and 5) or in the tariff on the key input of industry j (in columns 2, 4 and 6). To construct $\Delta\tau_{j,t}$, we use the variable $Dummy_{i,t}$ (columns 1-2), $Count\ of\ Products_{i,t}$ (columns 3-4) and $Import\ Coverage_{i,t}$ (columns 5-6). The sample covers all downstream industries for 1988-2016. 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 tariffs on downstream industries
(controlling for MFN, all TTBs, all inputs)

	Controlling for MFN		All TTBs		All inputs	
	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\tau_{j,t}$	-0.118***	-0.021***	-0.142***	-0.025***	-0.122***	-0.021***
	(0.044)	(0.005)	(0.053)	(0.006)	(0.044)	(0.005)
SIC4 FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,351	3,351	3,351	3,351	3,351	3,351
KP F-statistic	40.4	2,045.7	138.0	1,394.7	155.1	2,123.7

Notes: The table reports 2SLS estimates. The dependent variable $\Delta L_{j,t}$ is the annualized log change in employment in SIC4 industry j during the term ending in year t. $\Delta\tau_{j,t}$ is the change in the average input tariff of industry j (in columns 1 and 3) or in the tariff on the key input of industry j (in columns 2 and 4). $\Delta\tau_{j,t}$ is constructed using AD duties applied by the US on imports from all countries (in columns 1 and 2), all TTBs (AD duties, countervailing duties, and safeguards) applied by the US on imports from China (in columns 3 and 4), and including AD duties applied to non-manufacturing inputs (in columns 5 and 6). The sample covers all downstream industries for 1988-2016. 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 tariffs on downstream industries
(alternative methodology and clusters)

	Year differences		SIC2 clusters		SIC4 clusters	
	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\tau_{j,t}$	-0.473***	-0.084***	-0.118**	-0.021***	-0.118***	-0.021***
	(0.177)	(0.021)	(0.050)	(0.005)	(0.040)	(0.006)
SIC4 FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,407	13,407	3,351	3,351	3,351	3,351
KP F-statistic	143	2,052.2	164.4	1,709.9	347.2	5211.5

Notes: The table reports 2SLS estimates. In columns 1 and 2, the dependent variable, $\Delta L_{j,t}$, is the log change in employment in SIC4 industry j between years t and $t-1$; in columns 3 and 4, it is the annualized log change in employment in SIC4 industry j during the term ending in year t. $\Delta\tau_{j,t}$ is the change in the average input tariff of industry j (in columns 1 and 3) or in the tariff on the key input of industry j (in columns 2 and 4). The sample covers all downstream industries for 1988-2016. Standard errors are clustered at the SIC3 level in columns 1-2, SIC2 level in columns 3-4, and SIC4 level in columns 5-6. ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-14

The impact of tariffs on downstream industries
(alternative IO linkages)

	Total requirements		Including diagonal	
	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input
	(1)	(2)	(3)	(4)
$\Delta\tau_{j,t}$	–0.162***	-0.023***	-0.121***	-0.020***
	(0.060)	(0.006)	(0.044)	(0.005)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,351	3,351	3,351	3,351
KP F-statistic	201,3	2,012.9	148.4	1,743.2

Notes: The table reports 2SLS estimates. The dependent variable $\Delta L_{j,t}$ is the annualized log change in employment in SIC4 industry j during the term ending in year t. $\Delta\tau_{j,t}$ is the change in the average input tariff of industry j (in columns 1 and 3) or in the tariff on the key input of industry j (in columns 2 and 4). In columns 1 and 2, we use the total requirement coefficients $\theta_{i,j}$ to construct $\Delta\tau_{j,t}$ (excluding $\theta_{j,j}$), while in columns 3 and 4 we use the direct requirement coefficients $\omega_{i,j}$ (including $\omega_{j,j}$). The sample covers all downstream industries for 1988-2016. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.