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 all US tariffs since the 1980s 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 indicate that during 1988-2016 around 570,000 US jobs were lost in downstream industries due to AD duties against China in upstream industries, with the largest losses suffered by non-manufacturing sectors that rely heavily on protected inputs. Since President Trump took office, around 200,000 additional jobs were lost in downstream industries due to AD protection against China.

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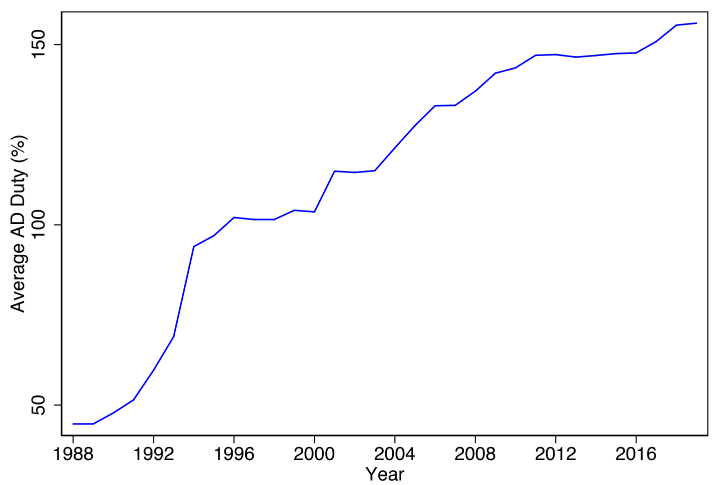
1 Introduction

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.*, 2019; 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, China had already been the target of increasing US protection: 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, average US antidumping (AD) duties against China increased from 44.8% to 147.7%.

Figure 1

Average US AD duty against China (1988-2019)



Notes: The figure plots the average AD duty applied by the United States 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" ... "tariffs on steel and aluminium have so disrupted markets that plans to expand BCA are on hold, costing American jobs."[1]

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

Such concerns are exacerbated by 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.[2]

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 how to address 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 both with 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 when they are sourcing these inputs domestically.[3] These firms will then try lobby for lower 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.[4] 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.[5] On the supply side, the literature on political economy of trade policy shows that US decisions on 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.

[2]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 in favor of intermediate inputs, such as primary metals, machinery, computer products, and electrical equipment (Fajgelbaum *et al.*, 2020).

[3]As shown by Amiti *et al.* (2019), higher import tariffs increase the price charged not only by foreign exporters, but also by domestic import-competing producers.

[4]For example, in 2006 "steel antidumping duties in the US 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).

[5]Trimarchi (2020) examines the impact of tariffs on imports and employment in protected industries during the 1988-2016 period. By contrast, we examine the impact of tariffs on vertically-related industries. Moreover, we consider other industry outcomes and extend the sample period to include tariffs introduced during the Trump's presidency.

Muûls and Petropoulou, 2013; Conconi *et al.*, 2017; Ma and McLaren, 2018; Fajgelbaum *et al.*, 2020). We exploit differences in vote outcomes of the presidential elections between 1988 and 2016, which generate exogenous variation in the identity of swing states and thus in the political importance of industries over time. The intuition is that, when a petition is filed by industries that are important in battleground states, the two key institutions involved in AD decisions – the US Department of Commerce and the US International Trade Commission – are more likely to rule to rule in favor of AD and to apply higher duties.

On the demand side, we exploit variation across industries in their experience at filing 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 helps to deal with concerns about the validity of the instrument.[7] Moreover, exploiting information on the historical AD experience of different industries improves the power of the instrument, allowing us to better predict the observed variation in protection.

We collect detailed information on all the tariffs applied by the US during the last decades. In our our main analysis, we focus on AD duties applied against China during the last seven complete presidential terms covering the 1988-2016 period. AD are by far the most common type of temporary trade barrier used during this period (see Figure A-2).[8] In robustness checks, we extend the analysis to other TTBs, other target

[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]If the instrument was solely based on variation in the importance of industries in swing states, one may be concerned that it could be picking up the effects of other federal policies (e.g. transfers) that could be skewed towards the interests of key industries in swing states.

[8]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

countries, and to tariffs introduced since President Trump took office. We combine the information about tariffs with disaggregated US input-output data, which allows us to identify vertical linkages between 479 industries and to construct different measures of input protection.

Our empirical results emphasize the importance of dealing with concerns about the endogeneity of trade policy. We show that, if we ignore these concerns, we 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 vertically-related industries.

Our baseline estimates indicate that a one percentage point increase in the average input tariff faced by an industry leads to a 0.11 percentage point decrease in the growth rate of employment in that industry. Alternatively, a one standard deviation increase in the average input tariff decreases the growth rate of employment by 0.34 percentage points per year, which corresponds to 21% of the average annual employment growth during our sample period. When considering all downstream industries, our estimates suggest that around 565,000 jobs were lost due to input protection. The effects are smaller (around 110,000 jobs) when restricting the analysis to manufacturing downstream industries. Within manufacturing, both blue- and white-collar jobs are affected. We further show that input tariffs have negative effects on other outcomes along supply chains. In particular, we find that AD duties in upstream sectors raise input prices and decrease sales and investment in downstream sectors.

Finally, we extend the analysis to include tariff measures introduced by the US since President Trump took office at the beginning of 2017. Our preliminary results suggest that, during this period, around 200,000 additional US jobs were lost in downstream industries due to AD protection against China. Quantifying the jobs lost due to the additional tariffs introduced by Trump since 2018 is more challenging, since the limited cross-industry variation of these tariffs makes it difficult to apply our instrumental variable approach.

The rest of the paper is structured as followed. In Section 2 we briefly review the related literature. In Section 3, we describe the data and variables used in our empirical analysis. Section 4 discusses the identification strategy, and Section 5 presents the

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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.

empirical results. Section 6 concludes, outlining some areas of future research.

2 Related Literature

Our paper is mainly related to three 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.* (2019) study the impact of the US-China trade war on prices and welfare. Using detailed (HS 10-digit) 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] Using detailed producer price index (PPI) data, they also show that the 2018 tariffs increased the prices charged by US producers. Two channels are behind this increase in domestic prices: first, higher tariffs on the inputs used by an industry lead to higher prices in that industry, suggesting that producers pass on the increase cost of importing inputs to consumers; second, domestic producers raise their prices when competing import prices rise due to higher tariffs. 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 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; combined with retaliation by trading partners, that led to a relative loss in manufacturing jobs. Similarly, Flaaen *et al.* (2020) estimate the price effect of US import restrictions on washing machines (the 2018 Trump's tariffs as well as the 2012 and 2016 antidumping duties against South Korea and China).

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 2018-2019 tariffs. Second, we study the

[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.* (2014) find substantial negative domestic product price effects from trade liberalization in India.

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 related to 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; 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.*, 2017; Erbahar and Zi, 2017; Conconi *et al.*, 2018; Vandenbussche and Viegelahn, 2018; Barattieri and Cacciatore, 2019). We contribute to this literature by exploiting a rich dataset covering all tariffs introduced by the US during the 1980-2019 period and employing an instrumental variable approach to deal with endogeneity concerns.

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 temporary trade barriers (e.g. Finger *et al.*, 1982; Bown and Crowley, 2013). Various papers in this literature have emphasized 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) and that experience at filing petitions is key for an industry's success at getting protection (e.g. Blonigen and Park, 2004 and 2016; Besedes *et al.*, 2017). Following Trimarchi (2020), we instrument trade protection by exploiting exogenous time variation in the political importance of different industries (resulting from changes in the identity of swing states across presidential terms) and cross-industry variation in historical experience at petitioning for AD duties.

3 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 of all tariffs 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 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.

3.1 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 demand 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 BEA six-digit industry codes into 4-digit SIC codes, to be able to combine input-output tables with industry-level data. This allows us to identify linkages between 479 industries, both inside and outside of manufacturing. 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.*, 2010; 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 ω_{ij} 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 will use this variable to capture direct vertical linkages between industries. In robustness checks, we will use total requirements coefficients, denoted with θ_{ij}, to allow for indirect linkages.

Figures A-3 and A-4 illustrate the average ω_{ij} across all SIC4 j industries, focusing respectively on the top-10 and top-50 most important inputs (i.e. with the highest ω_{ij}). Notice that the distribution of input-output linkages is highly skewed, with the most important input accounting for a much larger cost share.

3.2 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 United States, we can identify all the products covered at the 6-digit level of the Harmonized System (HS6).[11] We convert the tariff data from the HS6 classification into the 4-digit Standard Industrial Classification (SIC) to be able to identify input-output linkages and investigate the impact of protectionist measures on industry-level outcomes.[12]

In our main empirical analysis, we focus on AD duties introduced by the United States against China.[13] During the seven presidential terms covering the 1988-2016 period, the United States 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 measures and other countries targeted by the United States.[14] The top panel of Table A-1 reports descriptive statistics on US AD duties applied to imports from China during the last seven complete presidencies. The average level of the AD duty ($\tau_{i,t}$) is 15%, reaching up to 430%, with standard deviation of 53.

Since President Trump took office in January 2017, the United States has continued to target imports from China, initiating 31 new AD cases, and imposing 28 measures. The bottom panel of Table A-1 reports descriptive statistics on US AD duties applied to imports from China during Trump's presidency. Comparing these with the corresponding statistics in the top panel, we see that AD protection has further increased under Trump with an average AD duty ($\tau_{i,t}$) of 52%.

MFN tariffs

We have also collected data on Most-Favored-Nation (MFN) tariffs applied by the United States on imports from other GATT/WTO members. The source for MFN tariffs is the World Integrated Trade Solution (WITS) database, which combines information from the

[11]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 1989 it is at the 10-digit level of the Harmonized Tariff Schedule (HTS). We match TSUSA and HTS codes into HS6 codes. See Trimarchi (2020) for more details on the matching procedure.

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

[13]We use the "all others" AD rate. The results continue to hold if we use the average AD rate across exporters. This is not surprising, given the high correlation between the two rates (0.85).

[14]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).

UNCTAD TRAINS database (default data source) with the WTO Integrated Database (alternative data source).

MFN tariffs emerge from long rounds of multilateral trade negotiations: at the end of each round, governments commit not to exceed certain tariff rates; 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).

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 of the applied average 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 of the Uruguay Round of multilateral trade negotiations (1986-1994).

Section 201, 232, and 301 Tariffs under President Trump

In 2018 the Trump administration introduced tariffs on hundreds of goods under three rarely used US trade laws. We have collected information on these additional tariffs, which covered \$303.7 billion, or 12.6% of US imports in 2017 (Bown, 2019).

Some of Trump's tariffs have hit China exclusively, while others have hit China along with other countries. On February 7, it introduced 30% tariffs on solar panels and 20% tariffs on washing machines 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 broad 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 broad authority to impose tariffs against countries that make unjustified, unreasonable, or discriminatory trade actions. These were added on top of any AD duties already applying to Chinese imports.

It should be stressed that, relative to AD duties, the special tariffs introduced by Trump in 2018 vary much less across SIC4 industries, both at the extensive and intensive margin. When looking at the extensive margin, in 2018 Trump's tariffs were applied to 79% of manufacturing industries and covered on average 50% of products within an industry;[15] the corresponding shares for AD duties applied against China in 2018 were 22% and 5%. At the intensive margin, the average Trump's duty in 2018 was 11% (with a standard deviation of 7), while the average AD duty against China in the same year was 38% (with a standard deviation of 85).

3.3 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 $\textit{AD Duty}_{i,t}$ is the average AD duty applied by the US in year t against Chinese imports of good i.[16] Thus, $\sum_{i=1}^{N} \omega_{i,j}\ \tau_{i,t}$ is the average AD duty on inputs faced by downstream industry j.[17]

As mentioned before, the distribution of vertical linkages is highly skewed (see Figures A-3 and A-4). 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 the weights ω_{ij} used for the construction of the average input tariff (5) are based on the BEA 1992 Input-Output tables. The assumption that IO coefficients

[15] These shares were even higher (100% and 63%) in 2019.

[16] For a given SIC4 industry i, we construct $\textit{Duty}_{i,t}$ as an average of the AD duties applied to the HS6 goods in the industry.

[17] The set of N protected sectors is a subset of the 479 sectors in the economy, since tariffs are mostly applied to imports of manufacturing goods.

are time invariant can potentially bias our empirical analysis against finding significant negative effects of input tariffs on downstream industries. To the extent that final good producers can adjust the weights $\omega_{i,j}$ in the face of higher input protection, we would expect our estimates to be downward biased. Notice that our alternative measure of input protection should not suffer from this bias, since (6) only relies on IO coefficients to identify the key input.

Table A-5 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"), and 3714 ("Motor vehicle parts and accessories"), for which the average AD duty against China during the 1988-2016 period was respectively 81.61%, 76.93%, and 142.89%.

The variables $\textit{Average Input Tariff}_{j,t}$ and $\textit{Tariff on Key Input}_{j,t}$ captures 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 $\textit{AD Duty}_{i,t}$ in (1) with the following measures:

$\textit{Count of Products}_{i,t}$: number of HS6 goods in sector i covered by at least one AD duty against China in year t;

$\textit{Product Coverage}_{i,t}$: share of HS6 goods in sector i covered by at least one AD duty against China in year t;

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

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

3.4 Industry-Level Variables

To study industry-level employment, we follow Acemoglu *et al.* (2016) using data from the US Census County Business Patterns (CBP) for the seven complete presidential terms covering 1988-2016. When we extend the analysis to the ongoing term of President Trump, we use the Quarterly Census of Employment and Wages (QCEW) of the US

Bureau of Labor Statistics (BLS), which provides data up to the second quarter of 2019. The variable $Employment_{j,t}$ measures total employment in SIC4 industry j in year t.

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). The NBER-CES database also provides the variable $Cost\ of\ Materials_{j,t}$, which can be used as a proxy for the input prices faced by a downstream industry.[18]

4 Identification Strategy

4.1 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 pose 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 omitted variables 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.*, 2019). Final good producers (e.g. construction companies, car manufacturers) will thus lobby for lower tariffs on their inputs (e.g. steel, car parts), particularly if they stand to lose a lot from input protection.[19] If downstream firms successfully lobby against input protection, simple OLS coefficients will be biased upwards, making it harder to identify the negative effects of protection along supply chains.

[18]This variable is constructed using the use-make (input-output) and GDP-by-Industry data of the BEA. The use-make tables disaggregate each industry's total materials cost into the amount spent on each specific material. The share of each material in the industry's total materials cost is then used to weight each material's price index, resulting in a weighted-average price index for the industry's total materials cost.

[19]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).

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 antidumping and countervailing 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. A similar reasoning applies to positive productivity shocks experienced by US downstream producers: their expansion can lead to an increase in the volume of imports of intermediate inputs, which can result in an increase in tariffs.

4.2 Instrumental Variable

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

Supply for Protection

The variation on the supply side of AD protection comes from swing-state politics in the United States. As mentioned before, previous studies show that US trade policy is biased towards the interests of swing states and that AD duties respond to domestic political interests. Swing state politics can affect AD through the two institutions that regulate its administration: the US Department of Commerce (DOC) and the US International Trade Commission (ITC).[20] When the industry petitioning for AD duties is more important in swing states, the DOC may be more likely to rule in favor of dumping; in case of a positive ruling, it may also be willing to set a higher dumping margin, thus granting more protection.[21] ITC commissioners may also be more likely to rule positively on AD

[20]AD investigations in the US are conducted by two institutions: the DOC determines if there is dumping, i.e. if imported products are sold at less than the "fair value," and the ITC examines whether the relevant US industry has been materially injured, or threatened with material injury, as a result of the unfairly-traded imports. If both findings are affirmative, then an AD duty equal to the dumping margin established by the DOC is introduced.

[21]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

injury when the petition is filed by key industries in politically battleground states.

In line with previous studies (e.g. Conconi *et al.*, 2017; Ma and McLaren, 2018; Fajgelbaum *et al.*, 2020), we identify swing states using information on the outcome of presidential elections. In particular, we define a state to be swing in one term if the difference in the average vote shares of the two major parties in the previous presidential elections is less than 5%.

We measure the importance of an industry in swing states as the ratio of the total number of workers employed in industry i in all swing states s in year t, over the total number of workers in tradable sectors in swing states s:

$$Swing\ Industry_{i,t} = 100 * \frac{\sum_{s(t)} L_{s(t),i}}{\sum_{s(t)} \sum_i L_{s(t),i}}. \tag{3}$$

We fix industry employment shares at their 1988 levels. The variable $Swing\ Industry_{i,t}$ is meant to capture exogenous variation in supply for AD protection, coming from variation in the political importance of different industries. The 1988 employment shares pin down the importance of different industries across US states, while changes in the identity of swing states – coming from the margin of victory between Democratic and Republican candidates in Presidential elections – capture variation in the political importance of different states across terms.

Figure 2 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, one of the most heavily protected manufacturing sectors, with an average AD duty of 81.61% 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 limited or no employment in steel.[22] The map on the right is for construction, a large non-manufacturing sector that is not protected by AD duties, but relies heavily on steel as an input (SIC 3312 is the most important

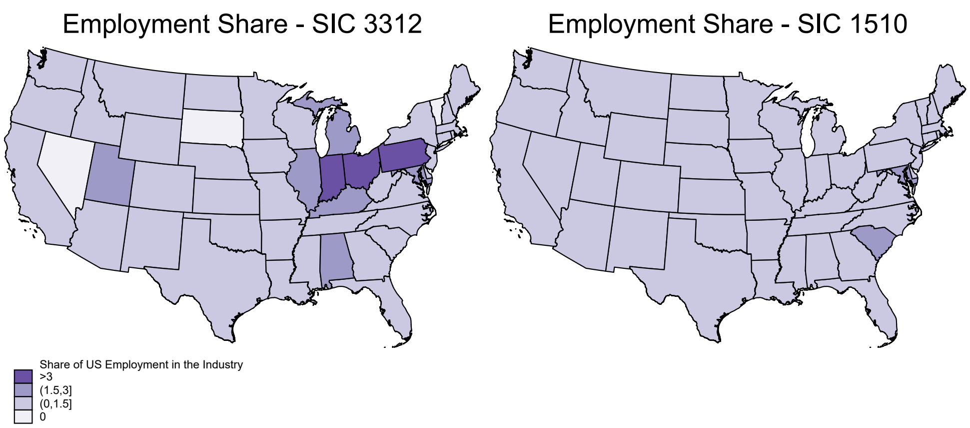
"like" product to the import good that is allegedly dumped. The DOC can initiate an investigation ex-officio, but this has happened rarely throughout our sample period (e.g. one of the rare examples is a case initiated in 2017 on aluminum plate from China).

[22]The mean of the ratio between state-level shares of US employment in steel and state-level shares of total US employment is 0.697. For Indiana, Ohio, and Pennsylvania, the ratio is respectively equal to 6.54, 4.69 and 3.16.

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.[23]

Figure 2

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 2 reflects a general pattern: final good industries are more dispersed than input industries. This can be seen by correlating the measure of industry upstreamness put forward by Antràs *et al.* (2012) with the index of industry spatial concentration from Ellison and Glaeser (1997). The correlation between the two measures is 0.24 (significant at the 1% level). When comparing industries based on their position along supply chains, more upstream industries are thus more geographically concentrated.

Figure 3 illustrates instead which states are classified as swing, based on the eight presidential elections between 1988 and 2016. Notice that both the number and identity of swing states vary significantly across terms.[24] These changes are driven by exoge-

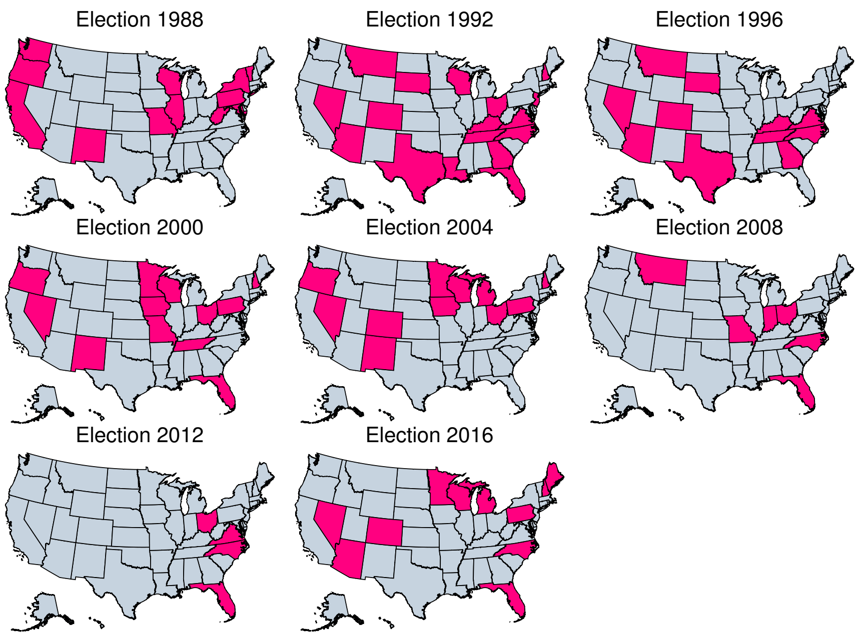
[23] The mean of the ratio between state-level shares of US employment in construction and state-level shares of total US employment is 0.998. The maximum ratio is 1.69 (for Maryland).

[24] 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

nous political variables (e.g. candidates' appeal) affecting differences in Democratic and Republican vote shares in a given state.

Figure 3

Swing states in US Presidential Elections (1988 to 2016)



Notes: The maps indicate in red the states that are classified as swing (less than 5% difference in the average vote shares of the two major parties) based on the last eight presidential elections.

The logic of the first component of our instrument ($Swing\ Industry_{i,t}$) is that, within an electoral term, the DOC and the ITC should be more willing to rule positively on AD – and to apply higher duties in case of a positive ruling – when the industry petitioning is more important (based on 1988 employment shares) in states classified as swing during that term (based on the vote shares of the two political parties in the previous presidential elections).

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 complexity of the the legal and institutional of US AD procedures, industries with prior

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.

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). There is important cross-sectional variation in the number of AD cases initiated during this period. More petitions were filed by industries that were at the time 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 that covered the textiles and apparel sectors). To ensure exogeneity of the instrument, we exclude petitions targeting China and leading to measures in force after 1988.

Our experience variable is the count of AD petitions filed by industry i during the 1980-1987 period:

$$Experience_i = \sum_{t=1980}^{1987} AD\ Petitions_{i,t}. \tag{4}$$

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.

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 pathways to AD protection (higher $Experience_i$).

Tables A-3 and A-4 in the Appendix provide lists of the top-10 SIC 4 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 both have experience at filing for AD protection (respectively ranked 2$^{\text{nd}}$ and 1$^{\text{st}}$ 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 – do not receive any protection (average AD duties are equal to 0).

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

$$IV\ Average\ Input\ Tariff_{j,t} = \sum_{i=1}^{N} \omega_{ij}\ Swing\ Industry_{i,t} \times Experience_i, \tag{5}$$

$$IV\ Tariff\ on\ Key\ Input_{j,t} = Swing\ Industry_{1,j,t} \times Experience_{1,j}. \tag{6}$$

where ω_{ij} in (5) denotes the direct requirement coefficient for the sector pair ij and $1, j$ in (6) 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.

Combining $Swing\ Industry_{i,t}$ with $Experience_i$ also allows us to deal with concerns about the external validity of the instrument. If we were to rely solely on variation in the political importance of an industry, resulting from changes in the identity of swing states across electoral terms, we could be confounding the effects of AD with other federal policies (e.g. transfers) that may be used to favor key industries in swing states. Against this concern, we only exploit variation in $Swing\ Industry_{i,t}$ only to the extent that it is relevant for AD protection. Indeed, 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 ($Experience_i = 0$).

4.3 Two-stage Least Squares: Term Differences

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.[25] We then estimate the following two-stage least squares (2SLS) specification:

$$\begin{aligned} \Delta L_{j,t} &= \beta_0 + \beta_1 \widehat{\Delta\tau_{j,t}} + \delta_j + \delta_t + \varepsilon_{j,t}, \\ \Delta\tau_{j,t} &= \beta_0 + \beta_1 \Delta IV_{j,t} + \delta_j + \delta_t + \varepsilon_{j,t}, \end{aligned} \tag{7}$$

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, and $\widehat{\Delta\tau_{j,t}}$ is its predicted value from the first stage. The instrument $\Delta IV_{j,t}$ is the change in *IV Average Input Tariff*$_{j,t}$ (or *IV Tariff on Key Input*$_{j,t}$) over term t. 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 variables and political conditions across presidencies. We cluster the standard errors at the SIC3 level to allow for correlated industry shocks (221 clusters).

5 Empirical Analysis

5.1 Main Results

We first ignore concerns about the endogeneity of trade policy and estimate the following Ordinary Least Squares (OLS) regression:

$$\Delta L_{j,t} = \beta_0 + \beta_1 \Delta\tau_{j,t} + \delta_j + \alpha_t + \varepsilon_{i,t}, \tag{8}$$

where variables are defined as in (7). As discussed in the previous section, the OLS estimates of β_1 cannot be interpreted causally and are likely to suffer from a positive bias, which should make it harder to identify the negative effect of tariffs along supply chains. This bias can be the result of omitted variables (e.g. lobbying by final good producers, productivity shocks in upstream or downstream industries), which can be correlated with both $\Delta L_{j,t}$ and $\Delta\tau_{j,t}$.

[25] I.e. for the term ending in year t, $\Delta L_{j,t} = \Big(\mathit{ln(Employment}_{j,t}) - \mathit{ln(Employment}_{j,t-4}) \Big)/4$.

Table 1

Input protection 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)
$\Delta\tau_{j,t}$	-0.012	-0.0003	-0.018	-0.001
	(0.013)	(0.0025)	(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 annual 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 results are reported in Table 1. In columns 1 and 2, we restrict the analysis to manufacturing downstream industries, while in columns 3 and 4 we consider all downstream industries. Across all specifications, the estimated coefficient for input protection is negative but not significant.

We next estimate (7) by 2SLS, using (5) and (6) to instrument for the change in input protection $\Delta\tau_{j,t}$. Table 2 reports the results of these regressions, following the structure of Table 1. 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.[26]

The last row of Table 2 reports the Kleibergen-Paap (KP) F-statistics to verify the predictive power of the instrument.[27] These are all 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-7 of the Appendix, we show the first-stage results of the 2SLS regressions in Table 2. As expected, the coefficients of both instruments are positive and significant at the 1% level in all specifications.

[26] AD duties are applied on top of MFN tariffs. The results of Table 2 are practically identical if we control for the MFN tariffs applied by the United States. This is not surprising given that during our sample period there is little variation in US MFN rates within SIC4 industries.

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

Table 2

The impact of input protection on employment in downstream industries (2SLS)

	Manufacturing sectors		All sectors	
	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input
	(1)	(2)	(3)	(4)
$\Delta\tau_{j,t}$	-0.064*	-0.014***	-0.108***	-0.021***
	(0.037)	(0.005)	(0.040)	(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	152.4	521.6	164.1	741.5

Notes: The table reports 2SLS estimates. The dependent variable $\Delta L_{j,t}$ is the annual 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.

Comparing Tables 1 and 2 shows that dealing with the endogeneity of trade policy is key to identifying the negative impact of tariffs along supply chains. The fact that the β_1 coefficient becomes negative and 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 to identify negative effects of upstream protection on employment growth in downstream industries.

Comparing across the specifications of Table 2, 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 less significant than the corresponding coefficient in column 3.

The baseline estimate of 0.108 reported in column 3 implies that a one percentage point increase in the average input tariff leads to a 0.11 percentage point decrease in the growth rate of employment in downstream industries. Alternatively, this specification implies that a one standard deviation increase in the average input tariff decreases employment growth by 0.35 percentage points, which explains 22% of the average annual employment growth during 1988-2016.[28]

[28] The number is computed by dividing the predicted change due to a one standard deviation in $\Delta\tau_{j,t}$ (-0.0035) in column 3 of Table 2 by the mean of $\Delta L_{j,t}$ (-0.016).

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

$$\textit{Employment Losses} = \sum_{j,t} L_{j,t}(1 - e^{-\beta_1 \widetilde{\tau}_{j,t}}), \tag{9}$$

where $L_{j,t}$ is the employment level in industry j at the end of term t, β_1 is the estimated coefficient of $\widehat{\Delta\tau_{j,t}}$ 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.[29]

If we use the baseline estimates in column 3 of Table 2 to carry out this counterfactual exercise, we find that around 570,000 US jobs were lost across all downstream industries due to input protection. The effects are smaller (around 110,000 jobs) if we use the estimates in column 1 of Table 2, which restricts the analysis to manufacturing downstream industries.

Table A-6 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 45.35% 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.

5.2 Robustness Checks

Table 2 shows that an increase in input tariffs leads to a significant decline in the growth rate of employment in downstream industries. In what follows, we discuss 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 2, omitting the specifications that restrict the analysis to manufacturing sectors.

The variables $\textit{Average Input Tariff}_{j,t}$ and $\textit{Tariff on Key Input}_{j,t}$ captures mostly variation in the intensive margin of protection. However, there is also considerable cross-

[29]Under the assumption that there is no measurement error and our instrument is valid, $\Delta\widetilde{\tau}_{j,t}$ is a consistent estimate of the contribution of exogenous politically-induced trade protection for AD-experienced sectors to changes in input protection.

industry variation in the extensive margin of AD protection. In Table A-8, we use the four alternative protectionist measures described in Section 3, 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-9, we verify that the negative effects of upstream protection on downstream employment are robust to including other countries targeted by US AD duties (see columns 1 and 2), as well as other TTBs (countervailing duties and safeguards) applied by the US against China (see columns 3 and 4).[30] Once again, the coefficient of $\Delta\tau_{j,t}$ is negative and significant in all specifications.

In another set of robustness checks, 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 focused on the effects of AD duties applied to all manufacturing input sectors different from j. The results reported in columns 1 and 2 of Table A-10 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 of the same table show that the results are also unaffected if we include the diagonal of the Input-Output matrix (i.e. ω_{jj}) when constructing these measures.

Finally, in Table A-11 we show that the results continue to hold when we change our dependent variable to yearly differences instead of term differences (columns 1-2), and when we use broader industry clusters at the SIC2 level (58 clusters; columns 3 and 4).

5.3 Alternative Outcome Variables

Our main results are focused on the impact of input protection on employment in downstream industries, in line with previous studies in the literature.

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

[30] 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.

We first estimate 2SLS regressions to examine the impact of input protection on blue- and white-collar jobs. The results are reported in Table 3. Notice that the number of observations in Table 3 is much smaller than in our baseline specification in column 3 of Table 2 (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.

Table 3
The impact of input protection on blue- and white-collar jobs in downstream industries

	Blue Collar		White Collar	
	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input
	(1)	(2)	(3)	(4)
$\Delta\tau_{j,t}$	-0.142**	-0.028***	-0.107*	-0.019**
	(0.061)	(0.006)	(0.058)	(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	131.7	687.3	131.7	687.3

Notes: The table reports 2SLS estimates. The dependent variable is the annual log change in the number of blue-collar and white-collar jobs 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 sectors. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

We next estimate 2SLS regressions to examine the impact of input protection on sales, investment, and input prices in downstream sectors. The results are reported in Table 4. In columns 1-4, we focus on sales and investment. 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 and investments along supply chains. In columns 5-6, we examine the impact of tariffs on the prices faced by producers in downstream industries, proxied by the variable *Cost of Materials*$_{j,t}$. The coefficient of $\Delta\tau_{j,t}$ is positive and significant, indicating that higher input tariffs raise input costs. This is in line with recent studies on the US-China trade war, which show that higher tariffs are associated with relative increases in producer prices via rising input costs (e.g. Amiti *et al.*, 2019; Flaaen and Pierce, 2019).

Table 4

The impact of input protection on sales, investment, and costs of downstream industries

	Sales		Investment		Cost of Materials	
	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)
$\Delta\tau_{j,t}$	-0.123*	-0.024***	-0.108	-0.034**	0.048***	0.004**
	(0.067)	(0.009)	(0.109)	(0.017)	(0.016)	(0.002)
SIC4 Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,320	2,320	2,320	2,320	2,320	2,320
KP F-statistic	131.7	687.3	131.7	687.3	131.7	687.3

Notes: The table reports 2SLS estimates. The dependent variable is the annual log change in sales (columns 1 and 2), investments (columns 3 and 4), and material costs (columns 5 and 6) 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 sectors. Standard errors are clustered at the SIC3 industry level; ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

5.4 Extending the Analysis to the Trump Administration

Our empirical analysis is focused on the effects of US AD duties against China during the last seven complete presidential terms covering the 1988-2016 period. In this section, we extend the analysis to tariffs introduced under the Trump administration. Due to the availability of the BLS data, the analysis covers up to second quarter of 2019.

As mentioned in Section 3, since President Trump took office in January 2017, China has been the target of even higher US AD protection. During this period, 31 new AD cases have been initiated and 28 new measures have been introduced; the average AD duty in force against China is 52%, with a maximum rate of 493% (see Table A-1).

In Table 5, we extend our benchmark 2SLS results to the AD duties introduced against China during Trump's presidency. Similarly to Table 2, we find that the negative effects of input protection are more easily identified when we include all downstream industries (columns 3 and 4). In our baseline specification of column 3, the coefficient of $\Delta\tau_{j,t}$ implies that a one percentage point increase in the average input tariff leads to a 0.12 percentage point decrease in the growth rate of employment in downstream industries. Using this estimate to carry out the counterfactual exercise in equation (9), we find that 203,858 additional US jobs were lost across downstream industries due to input protection since President Trump took office.

Table 5

The impact of input protection on employment in downstream industries (1988-2019)

	Manufacturing sectors		All sectors	
	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input
	(1)	(2)	(3)	(4)
$\Delta\tau_{j,t}$	-0.063*	-0.018**	-0.118***	-0.026***
	(0.038)	(0.008)	(0.045)	(0.008)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,132	3,132	3,828	3,828
KP F-statistic	185.2	526.7	182.5	707.9

Notes: The table reports 2SLS estimates. The dependent variable $\Delta L_{j,t}$ is the annual 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 on US AD duties against China. The sample covers 1988-2019 (second quarter). 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.

Recall that the baseline estimates in column 3 of Table 2 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 7 complete presidential terms. The results of Table 5 indicate that the AD duties introduced during the first two years and a half of Trump's presidency caused much larger losses along supply chains.

We have also tried to account for the losses due to the additional tariffs introduced by the Trump administration in 2018, which were added on top of AD duties and any other tariffs. As mentioned in Section 3, these special tariffs vary much less than AD duties across SIC4 industries, both at the extensive margin (they cover many more industries and a larger share of products within industries) and at the intensive margin (the duties are lower and vary little across products and sectors). The limited cross-industry variation makes it hard to use our IV strategy to predict Trump's tariffs. We can, however, instrument the total level of protection in a SIC4 industry (AD duties plus Trump's tariffs). When we do so, the 2SLS estimates are very similar to those in Table 5 (see Table A-12 in the Appendix).

6 Conclusions

The ongoing US-China trade war triggered by the tariffs introduced by President Trump in 2018 has stimulated a heated academic debate on the costs of protection. In this paper, we have studied the effects of protection along supply chains, exploiting the fact that, well before Trump took office, the United States has heavily used AD duties and other TTBs to protect some industries against competition from Chinese imports.

Our analysis emphasizes that addressing concerns about the endogeneity of trade policy is key to identifying the impact of tariffs along supply chains. We find 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 tariffs – exploiting exogenous variation in the political importance of different industries and their ability to petition for TTBs – we find large and significant negative effects. We show that our 2SLS results are robust to different measures of protection, vertical linkages, set of targeted countries, and econometric methodologies.

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 565,000 US jobs in downstream industries. The effects are smaller (around 110,000 jobs lost) when 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 documented by Trimarchi (2020). His estimates for the 1988-2016 period suggest that US AD duties against China saved around 22,000 jobs in the protected industries. When extending the analysis to AD duties introduced by the US against China since Trump took office, we find that around 204,000 additional jobs were lost across US downstream industries.

Our results resonate with arguments often heard in the media. Following President Trump's announcement of new tariffs on steel and aluminum imports in March 2018, many steel- and aluminum-using industries raised concerns about the damage these tariffs could inflict on them. For example, the National Tooling and Machining Association and the Precision Metalforming Association said in a joint statement: "President Trump campaigned on the promise to protect manufacturing jobs but ... his plan to impose tariffs will cost manufacturing jobs across the country.[31] Their statement also emphasized that there were 6.5 million workers employed in steel- and aluminum-using industries in the US, compared to only 80,000 employed in the steel industry.

In line with this quote, our results indicate that protecting jobs in upstream industries comes at the cost of destroying jobs along supply chains. The quote is focused on the steel and aluminum tariffs introduced by the Trump administration and on the resulting job losses in downstream manufacturing industries. Our analysis shows that inputs like steel and aluminum have been heavily protected well before Trump, and that these tariffs have had negative effects along supply chains, not only in manufacturing industries.

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

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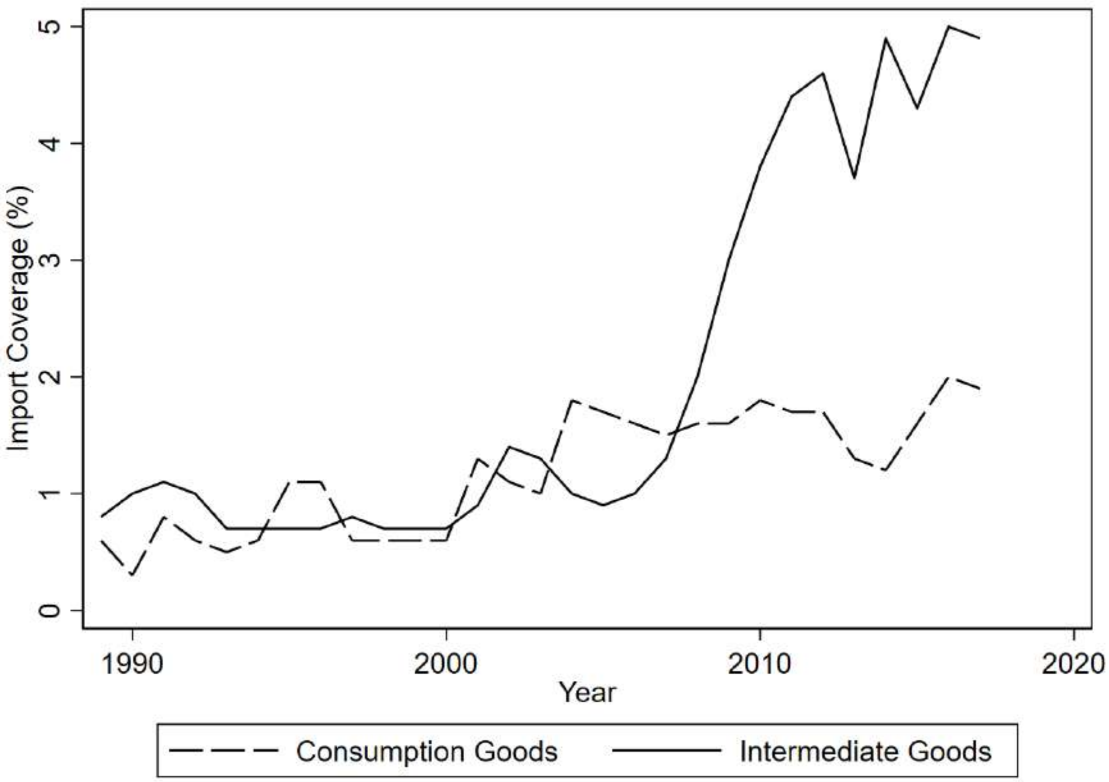
Appendix

Figure A-1

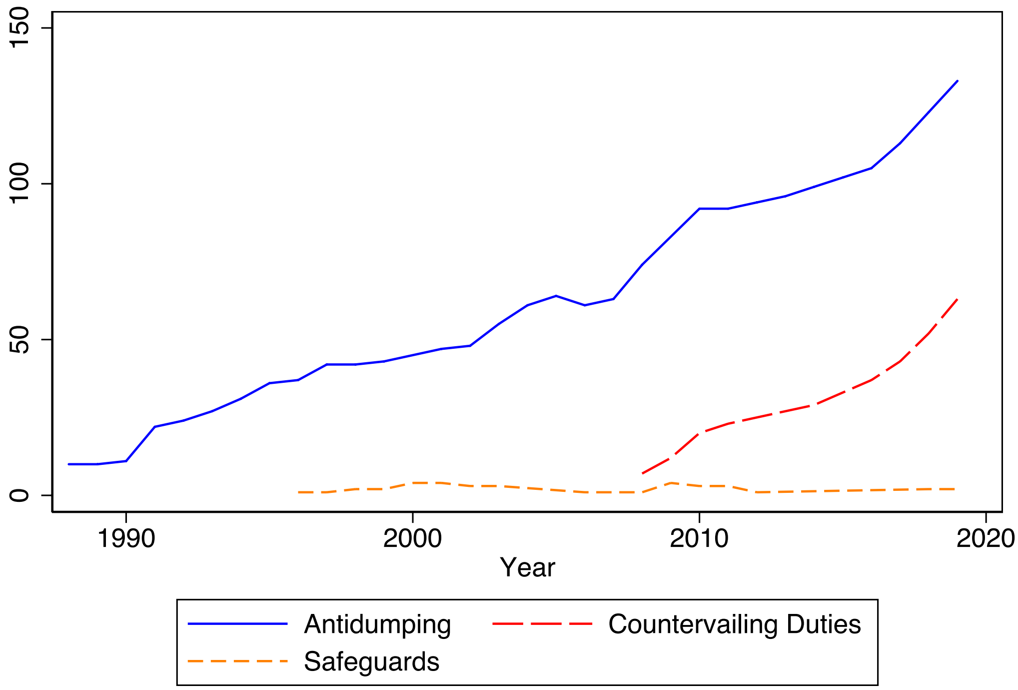
Share of US imports from China covered by temporary trade barriers (1988-2019)



Notes: The figure plots the share of US imports from China covered by AD 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

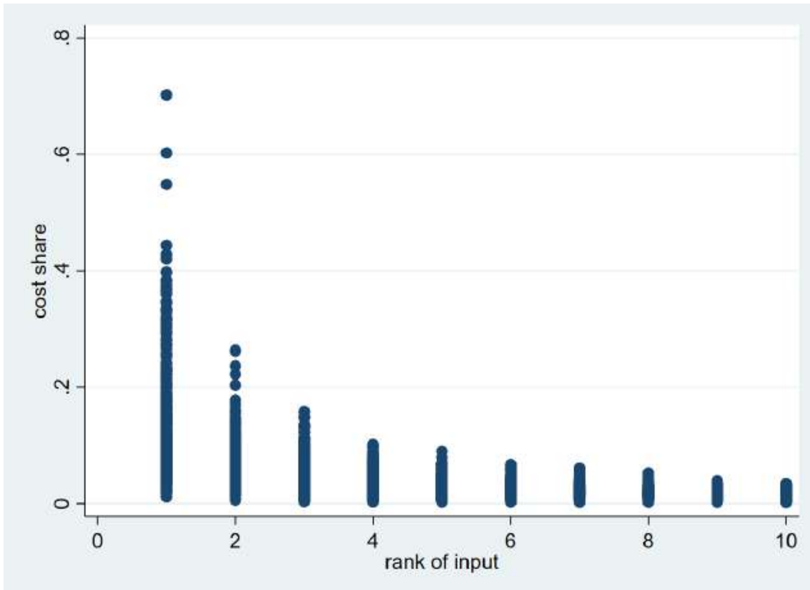
Number of US AD duties, countervailing duties, and safeguards against China (1988-2019)



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

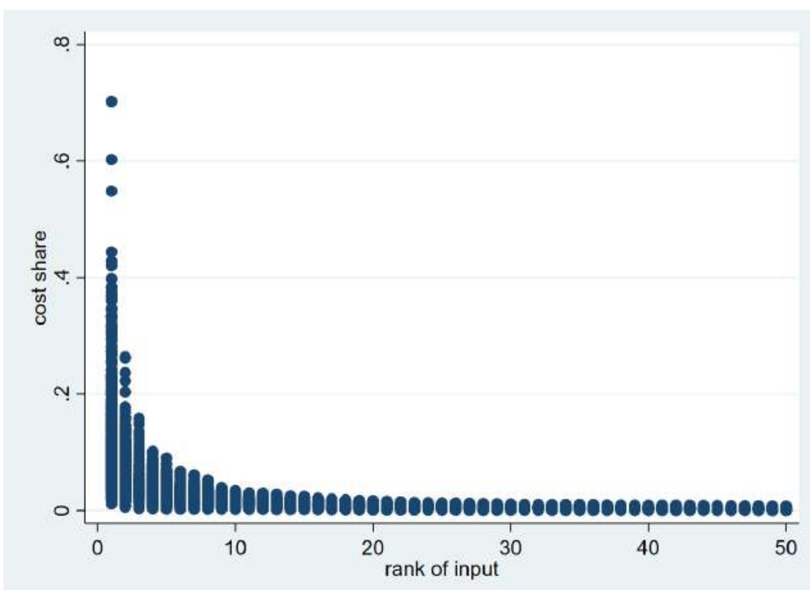
Average IO coefficients of the top-10 most important inputs



Notes: The figure plots the average direct requirement coefficients ω_{ij} across all 479 SIC4 j industries, focusing on the top-10 most important inputs $i(\neq j)$ for each industry j (i.e. highest ω_{ij}).

Figure A-4

Average IO coefficients of the top-50 most important inputs



Notes: The figure plots the average direct requirement coefficients ω_{ij} across all 479 SIC4 j industries, focusing on the top-50 most important inputs $i(\neq j)$ for each industry j (i.e. highest ω_{ij}).

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	0.53	0.00	4.30
Average Input Tariff ($\tau_{j,t}$)	0.14	0.16	0.00	1.17
Tariff on Key Input ($\tau_{1,j,t}$)	0.43	0.66	0.00	3.84
		2017-2019		
Variable	Mean	Std. Dev.	Min	Max
Tariff (τ_{it})	0.52	0.97	0.00	4.93
Average Input Tariff ($\tau_{j,t}$)	0.36	0.22	0.02	1.05
Tariff on Key Input ($\tau_{1,j,t}$)	1.04	0.88	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 (AD duties are only applied to these sectors), while the variable τ_{jt} can be constructed for all 479 industries in the economy.

Table A-2

Descriptive statistics on MFN tariffs applied by the United States

		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
		2017-2019		
Variable	Mean	Std. Dev.	Min	Max
Tariff (τ_{it})	0.05	0.25	0.00	3.50
Average Input Tariff ($\tau_{j,t}$)	0.01	0.03	0.00	0.42
Tariff on Key Input ($\tau_{1,j,t}$)	0.05	0.28	0.00	3.50

Notes: The table reports descriptive statistics on MFN tariffs applied by the United States 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 (AD duties are only applied to these sectors), while the variable τ_{jt} can be constructed for all 479 industries in the economy.

Table A-3

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

Sector	Description	$Swing\ Industry_{i,t}$	$Experience_i$	$Duty_{i,t}$ (%)
2752	Commercial printing, lithographic	0.0296	1	35.78
3089	Plastics products, n.e.c.	0.0277	3	1.461
2599	Furniture and fixtures, n.e.c.	0.0238	3	71.06
3714	Motor vehicle parts and accessories	0.0229	8	142.9
2711	Newspapers	0.0221	0	0
3711	Motor vehicles and car bodies	0.0174	2	0
3312	Blast furnaces and steel mills	0.0164	57	81.61
3812	Search and navigation equipment	0.0148	0	0
3499	Fabricated metal products, n.e.c.	0.0141	1	36.33
3599	Industrial machinery, n.e.c.	0.0127	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-4

$Experience_i$ - Top 10 Sectors

Sector	Description	$Swing\ Industry_{i,t}$	$Experience_i$	$Duty_{i,t}$ (%)
3312	Blast furnaces and steel mills	0.0164	57	81.61
3714	Motor vehicle parts and accessories	0.0229	8	142.9
3496	Misc. fabricated wire products	0.00288	6	114.7
2869	Industrial organic chemicals, n.e.c.	0.00454	6	125.1
2819	Industrial inorganic chemicals, n.e.c.	0.00410	5	68.95
2241	Narrow fabric mills	0.00134	5	59.78
3537	Industrial trucks and tractors	0.00150	4	0
2399	Fabricated textile products, n.e.c.	0.00154	4	59.78
3991	Brooms and brushes	0.000778	4	189.6
3069	Fabricated rubber products, n.e.c.	0.00708	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-5

Top-10 protected sectors, by average input duty

SIC4	SIC4 description	Average input duty	Average duty on key input	Key input SIC4	Key input description
3449	Miscellaneous metal work	50.24%	81.61%	3312	Blast furnaces and steel mills
2653	Corrugated and solid fiber boxes	45.35%	76.93%	2621	Paper mills
3711	Motor vehicles and car bodies	44.97%	142.89%	3714	Motor vehicle parts and accessories
2821	Plastics materials and resins	44.20%	125.09%	2869	Industrial organic chemicals, n.e.c.
3412	Metal barrels, drums, and pails	43.71%	81.61%	3312	Blast furnaces and steel mills
3448	Prefabricated metal buildings	43.15%	81.61%	3312	Blast furnaces and steel mills
2992	Lubricating oils and greases	41.61%	54.21%	2911	Petroleum refining
3715	Truck trailers	41.08%	142.89%	3714	Motor vehicle parts and accessories
2655	Fiber cans, drums and similar products	40.98%	76.93%	2621	Paper mills
2893	Printing ink	39.82%	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, and column 2 indicates the SIC4 description. Column 3 (column 4) shows the average input duty (average duty 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.

Table A-6

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

SIC4	SIC4 description	Share of total US employment	Average input duty	Employment loss due to average input tariffs
5812	Eating and drinking places	7.94%	50.24%	-60,378
1510	Construction	5.47%	45.35%	-51,056
5210	Retail trade	13.25%	44.97%	-44,946
5012	Wholesale trade	6.11%	44.20%	-26,900
8060	Hospitals	4.90%	43.71%	-20,551
7532	Auto repair	0.67%	43.15%	-16,358
8320	Social services	1.14%	41.61%	-9,725
2752	Commercial printing, lithographic	0.49%	41.08%	-9,302
3089	Plastics products, n.e.c.	0.49%	40.98%	-9,060
7371	Computer services	1.60%	39.82%	-8,512

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 predicted number of job losses, derived by applying our baseline result in column 3 of Table 2 to equation (9). Column 4 reports the sector's average share in total US employment, and column 5 indicates the average input duty faced by the sector.

Table A-7

First-stage results for Table 2

	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***	0.726***	0.001***	0.716***
	(0.000)	(0.032)	(0.000)	(0.026)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,742	2,742	3,351	3,351
Adj-R^2	0.25	0.18	0.24	0.16
KP F-statistic	152.4	521.6	164.1	741.5

Notes: The table reports the first-stage results of the 2SLS estimates reported in Table 2. 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 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-8

The impact of input protection on downstream industries
(alternative AD measures)

	Count of products		Product Coverage	
	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input
	(1)	(2)	(3)	(4)
$\Delta\tau_{j,t}$	-0.026***	-0.004***	-13.517*	-1.064***
	(0.010)	(0.001)	(7.903)	(0.276)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,351	3,351	3,351	3,351
KP F-statistic	186.5	6455.5	5.71	296.2
	Dummy		Import coverage	
	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input
	(1)	(2)	(3)	(4)
$\Delta\tau_{j,t}$	-0.143***	-0.028***	-4.717***	-0.921***
	(0.053)	(0.007)	(1.775)	(0.233)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,351	3,351	3,351	3,351
KP F-statistic	193.2	2425.6	125.1	626.4

Notes: The table reports 2SLS estimates. The dependent variable $\Delta L_{j,t}$ is the annual 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 (3 and 4) of the top panel, we use the variable $\textit{Count of Products}_{i,t}$ ($\textit{Product Coverage}_{i,t}$) to construct $\Delta\tau_{j,t}$, while in columns 1 and 2 (3 and 4) of the bottom panel, we use the variable $\textit{Dummy}_{i,t}$ ($\textit{Import Coverage}_{i,t}$). The sample covers all 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-9

The impact of input protection on downstream industries (all countries, all TTBs)

	All countries		All TTBs	
	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input
	(1)	(2)	(3)	(4)
$\Delta\tau_{j,t}$	-0.552***	-0.349**	-0.109***	-0.021***
	(0.203)	(0.170)	(0.040)	(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	80.9	5.84	161.2	734.9

Notes: The table reports 2SLS estimates. The dependent variable $\Delta L_{j,t}$ is the annual 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, $\Delta\tau_{j,t}$ is constructed using AD duties applied by the US on imports from all countries, while in columns 3 and 4 it is constructed using all TTBs (AD duties, countervailing duties, and safeguards) applied by the US on imports from China. The sample covers all 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-10

The impact of input protection 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)
$\Delta\tau_{j,t}$	-0.141***	-0.027***	-0.111***	-0.020***
	(0.053)	(0.007)	(0.040)	(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	123.1	142.9	169.5	674.6

Notes: The table reports 2SLS estimates. The dependent variable $\Delta L_{j,t}$ is the annual 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 θ_{ij} to construct $\Delta\tau_{j,t}$ (excluding θ_{jj}), while in columns 3 and 4 we use the direct requirement coefficients ω_{ij} (including ω_{jj}). The sample covers all 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-11

The impact of input protection on downstream industries
(alternative methodology and clusters)

	Year differences		SIC2 clusters	
	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input
	(1)	(2)	(3)	(4)
$\Delta\tau_{j,t}$	-0.435***	-0.084***	-0.108**	-0.021***
	(0.161)	(0.021)	(0.045)	(0.006)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	13,407	13,407	3,351	3,351
KP F-statistic	163.9	741.5	220.0	615.6

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 annual 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 industries for 1988-2016. Standard errors are clustered at the SIC3 (SIC2) industry level in columns 1-2 (3-4); ***, **, and * denote significance at the 1%, 5%, and 10% levels respectively.

Table A-12

The impact of input protection (AD duties plus Trump tariffs) on employment in downstream industries (1988-2019)

	Manufacturing sectors		All sectors	
	Average input tariff	Tariff on key input	Average input tariff	Tariff on key input
	(1)	(2)	(3)	(4)
$\Delta\tau_{j,t}$	-0.060*	-0.019**	-0.107***	-0.028***
	(0.036)	(0.008)	(0.040)	(0.008)
SIC4 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,132	3,132	3,828	3,828
KP F-statistic	213.7	505.2	235.7	652.5

Notes: The table reports 2SLS estimates. The dependent variable $\Delta L_{j,t}$ is the annual 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 on US AD duties against China, as well as the additional tariffs introduced in 2018-2019. The sample covers 1988-2019 (second quarter). 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.