

# Self-Harming Trade Policy? Protectionism and Production Networks\*

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## Abstract

Using monthly, product-level data on antidumping, countervailing duties, and safeguards, we estimate the employment effects of protectionism both in protected industries and through vertical production linkages. We focus on NAICS 4-digit U.S. manufacturing industries. First, exploiting institutional details of temporary trade barriers regulation and the high-frequency nature of the data, we identify movements in protectionism that are plausibly free of endogenous and anticipatory movements. Second, by combining the identified shocks with input-output tables, we construct exogenous measures of protectionism faced by downstream producers. We then estimate panel local projections using the identified trade-policy shocks. We find that protectionism has small, short-lived, and mostly insignificant beneficial effects in protected industries. In contrast, protectionism has sizable and significant negative effects in downstream industries. The employment decline follows an increase in the price of intermediate-inputs and final goods.

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# 1 Introduction

In 2018, the U.S. administration imposed new tariffs on roughly 12% of imports, sparking debates on the effects of protectionism to unprecedented levels. A distinguishing feature of recent U.S. trade policy is the focus on the access to global supply chains (Krugman, 2018, and Baldwin, 2018). For instance, tariffs against Chinese imports have heavily targeted intermediate inputs, with nearly \$50 billion of imports of steel and aluminium being affected (Bown, 2018a). Such a shift of trade protection towards intermediate inputs is not limited to the recent past. Hidden behind unchanging tariff policies, governments used temporary trade barriers (TTBs)—antidumping, countervailing duties, and safeguards—to restrict trade in intermediate inputs in the last two decades (Bown, 2018b). In particular, while governments have maintained lower tariffs on factor inputs relative to final goods, TTBs on imported intermediates have been on average higher and growing relative to TTBs on final goods.

In light of these events and considerations, it is not surprising that much of the discussion on the effects of protectionism contrasts potential gains in protected industries and possible negative effects on sectors that use protected goods as intermediate inputs.<sup>1</sup> Despite the relevance of supply-chains considerations in policy discussions, econometric evidence on the effects of protectionism through vertical production linkages is scant. The present paper addresses this issue. We study the employment effects of TTBs in protected industries as well as in industries that use the output of protected sectors as an input of production.

Our contribution to the literature is threefold. First, we provide novel evidence on the role of production networks in propagating protectionism targeted to specific industries. Second, while the trade literature typically focuses on the long-run effects of permanent tariff reductions, we provide evidence on the dynamic consequences of TTBs. Third, we exploit a novel high-frequency identification of temporary trade-policy shocks at a very disaggregated industry-level.

We use data on antidumping, countervailing duties, and global safeguards. Various reasons make TTBs well-suited for the purpose of our study. First, TTBs are the predominant contingent trade policy instrument for most WTO members (Bown, 2011). Second, TTBs are largely used in key upstream industries such as base metals and metal products, chemicals and allied products, and plastics and rubber products. As a result, TTBs provide an empirically-relevant measure of protectionism in upstream industries. Third, TTBs lead to the imposition of remarkably large

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<sup>1</sup>See, for instance, the Financial Times article “Thousands of Jobs At Risk Over Tariffs, U.S. Manufacturers Warn,” on March 1, 2018, available online at <https://www.ft.com/content/bd5984be-1d8f-11e8-aaca-4574d7dabfb6>.

tariffs, 10 to 20 times higher than MFN tariffs on average (Blonigen and Prusa, 2015). Fourth, the high-frequency nature of the data allows us to exploit institutional features of TTBs’ procedures that impose short-run restrictions relevant for the identification of exogenous trade policy shocks. Fifth, the use of TTBs allows us to conduct the analysis at a very disaggregated level—NAICS 4-digit industries—encompassing 70 narrowly defined manufacturing sectors. This level of aggregation substantially mitigates aggregation-bias concerns, allowing us to measure accurately input-output sectoral linkages.

We construct monthly time series for the sectoral import shares of products subject to new investigations using the World Bank’s Temporary Trade Barriers Database (Bown, 2016). The sample covers the period 1994-2015. We focus on investigations rather than on their final outcomes (e.g., duties), since the latter are likely to be anticipated by economic agents—for instance, the opening of TTBs investigation discloses evidence on the margins of dumping and/or foreign governments’ subsidies which determine the size of applied tariffs. Our benchmark measure of economic activity is industry-level employment growth, a key economic outcome in the policy discussions that motivate protectionism.

The analysis proceeds in three steps. First, we identify trade policy changes that are plausibly (i) unanticipated and (ii) not correlated with economic factors that affect industry-level employment. For want of a better term, we call these trade-policy changes “exogenous,” reflecting variation in TTBs that is plausibly free of endogenous and anticipatory movements. We consider two alternative (and complementary) approaches. One exploits within-industry time-series variation, while the other exploits the panel dimension of the data. In both cases, we build on a consolidated approach in the monetary policy literature, following the seminal work by Romer and Romer (2004). The idea is to purge the series of interest (in our case, the share of NAICS 4-digit imports subject to new investigations) of movements taken in response to current, previous, and future expected economic conditions. Regulation-induced lags in the opening of an investigation imply that TTBs cannot react to economic shocks within a month, thus removing simultaneity concerns. We then control for past economic conditions and also consider measures that capture expected economic outcomes. In particular, using firm-level data, we construct for each industry a benchmark measure of expected returns, the market-to-book ratio (e.g., Pontiff and Schall, 1998, and subsequent literature). When exploiting the panel dimension of the data, we also include industry and time fixed effects, stronger controls for unobserved heterogeneity and common shocks.

We combine the identified trade-policy shocks with NAICS 4-digit total requirements input-

output tables to construct a measure of average protectionism faced by downstream industries. By weighting TTBs shocks with information on the extent to which sectors use each others' output as an intermediate input, our approach mirrors the literature that studies the long-run effects of input-tariff reductions (e.g., [Amiti and Konings, 2007](#)). Out of the fifteen industries most affected by upstream protectionism, only three are also active users of temporary trade barriers.

Finally, we estimate panel local projections using the identified trade-policy shocks to determine the dynamic effects of protectionism on employment in protected and downstream industries. Since [Jorda \(2005\)](#)'s seminal article, local projections have become a popular and well-established tool to estimate impulse response functions in macroeconomics, and a growing number of studies applies this methodology with panel data (e.g., [Auerbach and Gorodnichenko, 2013](#), [Jorda and Taylor, 2016](#), [Leduc and Wilson, 2013](#), and [Ottonello and Winberry, 2018](#) just to name a few). The approach consists in running a sequence of predictive regressions of a variable of interest (e.g., industry-level employment) on a structural shock (e.g., protectionism) for different prediction horizons. Thus, local projections construct impulse responses as a direct multistep forecasting regression, providing a flexible and parsimonious approach that does not impose (potentially inappropriate) dynamic restrictions.

Our analysis yields three main results. First, protectionism has small and short-lived beneficial effects on industry employment on average. In our benchmark specification, an increase in the share of imports subject to TTBs equal to 2 percentage points (the average import share affected by TTBs in the episodes we analyze) leads to an average increase in industry employment by 0.15 percentage at the peak. The response turns negative after approximately 18 months. The effects are in general statistically insignificant. This finding is consistent with different explanations, including the fact that TTBs affect profits (e.g., markups) rather than output in protected industries, the presence of offsetting forces determining industry's output demand (e.g., expenditure switching and expenditure changing), as well as heterogenous responses across producers within an industry (e.g., a different exposure to products covered by TTBs).

Second, protectionism has negative, persistent, and statistically-significant effects on employment in downstream industries. Our estimates imply that a uniform 2 percentage-points increase in the share of imports subject to TTBs in all upstream industries, leads to an average employment decline equal to 0.8 percentage points after two years.

Finally, the employment decline in downstream industries is accompanied by a statistically significant increase in both intermediate-input and final producer prices. From a timing perspective,

the increase in prices precedes the decrease in employment, suggesting that it is indeed a loss of competitiveness that causes the employment decline in downstream industries. In addition, employment losses are larger on average when goods are more substitutable.

**Related Literature** Relatively few contributions study the relationship between trade policy and vertical production linkages. One strand of the literature focuses on the consequences of value chains for tariff settings. [Conconi, Garca-Santana, Puccio, and Venturini \(2018\)](#) show that rules of origin embedded in free-trade agreements (NAFTA) lead to a sizeable reduction in imports of intermediate goods from third countries. [Blanchard, Bown, and Johnson \(2016\)](#) show that global supply chains modify countries' incentives to impose import protection, since higher domestic value added in foreign final goods results in lower applied bilateral tariffs.<sup>2</sup> [Erbahar and Zi \(2017\)](#) show that protection granted to intermediate manufacturers leads to petition for protection by their downstream users. Finally, [Baqae and Farhi \(2019\)](#) study a large class of trade models with global production networks. They show that global value chains dramatically increases the welfare cost of protectionism. We contribute to this literature by providing empirical evidence on the effects of protectionism through vertical linkages, complementing the perspective of these studies.

Another strand of the literature focuses on the long-run productivity effects of trade liberalization in developing economies through price and availability of intermediate inputs (e.g., [Amiti and Konings, 2007](#), [Topalova and Khandelwal, 2011](#), and [Goldberg, Khandelwal, Pavcnik, and Topalova, 2010](#)). In contrast, we study the short-run effects of upstream protectionism on sectoral employment in an industrialized economy. In addition, there are important conceptual differences between temporary protectionism and trade liberalization. First, since trade liberalization episodes are permanent policy changes, they affect the present discounted value of income and profits differently from a temporary increase in trade barriers.<sup>3</sup> Second, while trade liberalization reduces tariffs against a large set of countries, protectionism targets selected exporters. Finally, trade liberalization typically occurs with other structural reforms, rendering more challenging the identification of the effects of a given policy change.

A recent literature studies the effects of protectionism abstracting from the role of production networks. A strand of the literature focuses on the trade effects of antidumping. [Durling and Prusa](#)

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<sup>2</sup>[Alfaro, Conconi, Fadinger, and Newman \(2016\)](#) exploit variation in the degree of trade protection faced by firms to show that the level of product prices affect vertical integration.

<sup>3</sup>For instance, [Lettau and Ludvigson \(2004\)](#) find that households' consumption changes by less in response to transitory income shocks relative to permanent income shocks. Similarly, the response of firms to cash flow shocks depends on whether shocks are transitory or permanent ([Decamps, Gryglewicz, Morellec, and Villeneuve, 2017](#))

(2006) and [Bown and Crowley \(2007\)](#) identify distinct trade effects of antidumping protection at the product level (i.e., trade destruction, trade diversion, and trade deflection), while [Lu, Tao, and Zhang \(2013\)](#) and [Vandenbussche and Zanardi \(2010\)](#) show that antidumping significantly affects aggregate trade volumes. Other studies focus on economic outcomes beyond trade. Part of this literature addresses the so-called “China Syndrome,” identifying the effects of rising Chinese import competition on U.S. local labor markets and the effects of protectionist trade policies in this context (e.g., [Trimarchi, 2018](#)). [Barattieri, Cacciatore, and Ghironi \(2018\)](#) study the effects of both TTBs and tariff changes on macroeconomic time series. In a related study, [Furceri, Hannan, Ostry, and Rose \(2018\)](#) estimate the macroeconomic effects of tariffs using local projections on annual data for a panel of countries.<sup>4</sup> Finally, few contributions study the effects of TTBs on the performance and behavior of protected firms.<sup>5</sup> With the exception of [Barattieri, Cacciatore, and Ghironi \(2018\)](#), all these studies focus on annual data and none of them addresses the effects of protectionism through input-output linkages.

Two important recent contributions analyze the impact of the 2018 trade war on U.S. prices, imports, and aggregate welfare. [Amiti, Redding, and Weinstein \(2019\)](#) find that the U.S. experienced substantial increases in the prices of intermediates and final goods, reductions in availability of imported varieties, and complete tariff pass-through on imported goods. [Fajgelbaum, Goldberg, Kennedy, and Khandelwal \(2019\)](#) estimate import demand and export supply elasticities using changes in U.S. and retaliatory tariffs over time. Using a general equilibrium framework that matches these elasticities, they find substantial aggregate and regional impacts of U.S. tariffs.<sup>6</sup> We complement the perspective of these studies by providing evidence on the dynamic effects of protectionism on economic activity in protected industries and through production networks.

Finally, our paper is also related to the burgeoning literature that studies the emergence of global value chains (e.g. [Alfaro, Conconi, Fadinger, and Newman, 2016](#), [Johnson and Noguera, 2012](#), and [Koopman, Wang, and Wei, 2014](#)) and their implications for aggregate dynamics (e.g., [di Giovanni and Levchenko, 2010](#)).

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<sup>4</sup>One of their specifications considers the role of vertical linkages at the 2-digit industry level. Our approach differs since we use disaggregated high-frequency data on TTBs. Moreover, we identify exogenous variations in trade policy exploiting institutional features of TTBs.

<sup>5</sup>[Konings and Vandenbussche \(2004\)](#) focus on markups, while [Pierce \(2011\)](#) studies the response of physical productivity. A few papers look at how TTBs affect foreign exporters’ pricing behavior ([Blonigen and Park, 2004](#)), export-destination diversification ([Bown and Crowley, 2006](#), and [Bown and Crowley, 2007](#)), and FDI strategies ([Blonigen, 2002](#)).

<sup>6</sup>[Huang, Lin, Liu, and Tang \(2018\)](#) study the financial-market response to the 2018 U.S. presidential memorandum that proposed tariffs on imported Chinese products. They find that industries that have a higher average share of imports across their upstream industries have a lower average cumulative raw return, suggesting indirect effects of perceived tariff-induced increases in input costs.

**Outline** The paper proceeds as follows. Section 2 reviews key features of the TTBs process. Section 3 outlines the empirical strategy for the identification of trade policy shocks. Section 4 presents the results on the effects of protectionism on employment outcomes. Section 5 provides evidence on the mechanisms behind the transmission of protectionism through vertical production linkages. Section 6 discusses the sensitivity of the results to alternative measures and empirical approaches. Section 7 concludes.

## 2 Background and Data on Temporary Trade Barriers

Antidumping duties, global safeguards, and countervailing duties—what [Bown \(2011\)](#) calls temporary trade barriers—are the primary policy exceptions to the trade rules embodied in the WTO. Countries have been using these policies to implement new trade restrictions during the last twenty years. Antidumping proceedings determine whether foreign exporters are selling goods in a country at less than fair value (“dumped”). Countervailing duties proceedings determine whether foreign governments are unfairly subsidizing their exporters. Global safeguards actions determine whether imports of a particular good are a substantial cause of injury, or threat thereof, to the domestic industry. Among TTBs, antidumping initiatives account for the vast majority of trade policy actions—across countries, they represent between 80 and 90 percent of all TTBs.

In the U.S., under the Tariff Act of 1930, industries can petition the government for relief from imports that are sold at less than fair value or which benefit from foreign governments’ subsidies. Petitions target specific imported products within an industry and can involve one or more trading partners. Once a petition is filed, the USITC conducts an assessment of compliance determining whether the petition satisfies all the requirements to open an investigation. If formal requirements are met, the USITC conducts a preliminary injury investigation to determine (1) whether there is a reasonable indication that the industry is materially injured, or (2) whether the establishment of the industry is delayed. If the USITC determination is affirmative, the Department of Commerce continues the investigation, which can lead to the imposition of tariff duties. Otherwise the investigation is terminated.

Concerning the timing of TTBs policy actions, three aspects are important for our analysis. Consider the case of antidumping for illustrative purposes (countervailing duties and global safeguards have identical procedures). First, the opening of an investigation features decision lags imposed by regulation. In particular, producers’ petitions must gather evidence about dumped imports and each petition must represent at least 25 percent of the product’s domestic total production



(USITC, 2015). The preliminary assessment of compliance by the USITC induces additional time lags. As a result, it takes longer than a month to open a new investigation. We will exploit such decision lags when identifying exogenous trade-policy changes. Second, the opening of an investigation is immediately announced to the public and agents can access the supporting evidence about the margins of dumping. The disclosure of the evidence implies that tariffs are predictable at the time of the investigation, since antidumping duties are commensurate to the margins of dumping. To avoid possible anticipation effects, we focus on investigations rather than on their final outcome.<sup>7</sup> Finally, imposed tariffs are in place for five years and the application of antidumping duties can be retroactive (up to the beginning of the investigation).

## 2.1 Descriptive Statistics

### 2.1.1 Temporary Trade Barriers in the U.S.

We construct monthly time series for products subject to new investigations using the World Bank’s Temporary Trade Barriers Database (Bown, 2016). Following Bown and Crowley (2013), we record the number of Harmonized System (HS) 6-digit products for which an investigation begins in a given month. We match the date of each investigation to the number of products covered by each investigation.<sup>8</sup> Using the conversion table constructed by Pierce and Schott (2009), we then aggregate the HS 6-digit classification to the NAICS 4-digit industry level. The sample covers the period 1994:1 until 2015:12. The balanced panel features  $T = 276$  observations and  $N = 70$  industries.

Table 1 presents descriptive statistics about TTBs’ investigations in selected NAICS 4-digit U.S. industries. We exclude global safeguards, since there are very few episodes in the sample, and such episodes constitute large outliers in some industries. In Section 6, we show that considering global safeguards does not qualitatively affect our results.

TTBs activity is fairly concentrated in a few industries—e.g., base metals and metal products, chemicals and allied products, and plastics and rubber products. For this reason, in Table 1, we consider the eight industries that feature the highest number of TTBs episodes in the sample period, accounting for approximately 70% of all investigations. The first column records both the

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<sup>7</sup>Whether or not the assumption has first-order effects depends on the time elapsing between the beginning and the end of an investigation. In the U.S., investigations typically last 45-60 days. Staiger and Wolak (1994) find that the mere opening of an antidumping investigation has effects on imports.

<sup>8</sup>In some cases, information on the products subject to investigation is available at a more disaggregated level (8- or 10-digits). Following Bown and Crowley (2013), we record such observations at the HS-6 level whenever at least one sub-product is subject to the investigation.



number of TTBs episodes (i.e., the number of months with at least one new investigation in a given industry) and the total number of products under investigation within each industry (reported in brackets). The most heavy user of TTBs is the industry “Iron, Steel and Ferro-Alloy,” which accounts for approximately 50% of all investigations.

Table 1: Top TTBs Users, Descriptive Statistics

Top TTBs Users (NAICS-4)	Episodes (Products)	% Success	Median Tariff	Average Import Share	Max Import Share	2007 Sectoral Imports/Output
Iron, Steel and Ferro Alloy (3311)	60 (457)	82%	35.1%	1.87%	8.89%	33.55%
Basic Chemical (3251)	44 (63)	75%	101.0%	0.21%	2.26%	14.56%
Other Fabricated Metals (3329)	15 (28)	80%	57.5%	1.53%	8.14%	37.04%
Steel Products From Purchased Steel (3312)	11 (33)	64%	27.9%	11.09%	31.50%	8.61%
Resin, Rubber, Fibers (3252)	10 (14)	90%	24.8%	1.04%	3.18%	14.56%
Spring and Wire Products (3326)	9 (11)	100%	116.3%	7.23%	21.33%	36.49%
Arch., Constr. and Mining Machinery (3331)	8 (21)	88%	193.5%	1.34%	4.97%	59.37%
Nonferrous Metal Production (3314)	7 (17)	100%	60.5%	2.11%	5.47%	64.99%

The second column in Table 1 shows that, across industries, a very large share of TTBs episodes end up with the imposition of duties. For instance, in the “Iron, Steel and Ferro-Alloy,” the figure is 82%. In other industries, all episodes led to the imposition of tariffs. The applied tariff rates are also substantial, reaching up to 193% in “Agriculture, Construction, and Mining Machinery” (see the third column).

Columns 4 and 5 of Table 1 provide information on the intensive margin of investigations. Column 4 reports the average sectoral import share affected by TTBs episodes. Column 5 reports the maximum value of this import share. The largest average import coverage occurs in “Steel Product Manufacturing from Purchased Steel” (13.68%), with a peak equal to 31.5%. For the most important user of TTBs (“Iron, Steel and Ferro-Alloy”), TTBs episodes on average involve approximately 2% of industry imports, although the largest episode covers 9% of imports. Finally, column 6 shows that the top TTBs users are in general substantial importers.

## U.S. Production Network (2007)

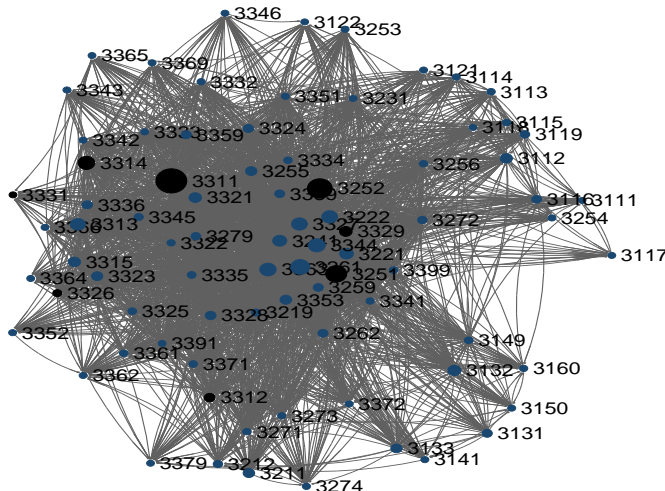


Figure 1. Production network implied by 2007 NAICS 4-digit input-output tables.

### 2.1.2 TTBs Users and Production Linkages

We now turn to the relevance of TTBs for downstream industries. Figure 1 plots the U.S. production network for the year 2007, showing the linkages between each manufacturing industry and the sectors that use industry’s output as an intermediate input. Each circle in the network has a quantitative interpretation, since a larger circle implies a larger cumulative input usage by downstream industries. The figure shows that industries that use most heavily TTBs protection have a central role in the production network.

Table 2 provides quantitative information about the contribution of these industries as intermediate-input suppliers in the manufacturing sector. We use the 2007 direct-requirements input-output table from the U.S. Bureau of Economic Analysis.<sup>9</sup> Each  $(i, j)$ th cell in the table gives the amount of a commodity in row  $i$  required to produce one dollar of final output in column  $j$ . We aggregate the direct-requirements table at the NAICS 4-digit level. In addition, we construct a standard total-requirements table.<sup>10</sup> The total-requirements table records both the direct requirements (e.g., how much “Steel&Iron” is needed to make one dollar’s worth of “Motor Vehicle Parts”) as well as the indirect requirements (e.g., if it takes “Steel&Iron” to make “Transmission Equipment”, and the latter is an input of “Motor Vehicle Parts,” then “Motor Vehicle Parts” uses “Steel&Iron” as an

<sup>9</sup>Benchmark input-output tables at the level of aggregation of our data are available only every five years. The year 2007 is the closest to the mid point of our sample period.

<sup>10</sup>Let  $D$  be the direct-requirements table. The total-requirements table is then given by:  $T = D[I - D]^{-1}$ , where  $I$  is the identity matrix.

input indirectly). By construction, no cell in the total-requirements table can take on values greater than one.

The first column in Table 2 measures the output share of each industry relative to total U.S. manufacturing output in 2007. Column 2 and 3 report the average direct requirements for each industry and the maximum requirement across downstream users, respectively. Column 4 and 5 report analogous figures using total requirements. As shown by the table, the largest TTBs users are important intermediate-input suppliers. For instance, the top user (“Iron, Steel and Ferro-Alloy”) accounts for approximately 6% of all intermediate inputs used by other industries on average (see column 4), while the maximum input share is 45%. In total, for the top TTBs users, the intermediate-input share averages to approximately 25% (column 4), whereas the same industries account for approximately 10% of manufacturing output (column 1).

Table 2: Top TTBs Users, Vertical Linkages

Top TTB Users (NAICS-4)	NAICS-4 Output Share	NAICS-4 Av. Input Share Direct Req.	NAICS-4 Max Input Share Direct Req.	NAICS-4 Av. Input Share Total Req.	NAICS-4 Max Input Share Total Req.
Iron, Steel and Ferro Alloy (3311)	1.96%	3.21%	35.70%	5.93%	44.80%
Basic Chemical (3251)	1.92%	1.84%	44.72%	8.38%	84.56%
Other Fabricated Metals (3329)	1.32%	0.66%	3.63%	1.17%	4.77%
Steel Products From Purchased Steel (3312)	0.17%	0.42%	17.68%	0.68%	19.15%
Resin, Rubber, Fibers (3252)	1.92%	2.36%	36.77%	4.23%	41.78%
Spring and Wire Products (3326)	0.43%	0.17%	6.85%	0.24%	7.38%
Arch., Constr. and Mining Machinery (3331)	1.59%	0.003%	0.255%	0.23%	1.00%
Nonferrous Metal Production (3314)	1.10%	1.26%	18.29%	4.04%	35.59%
<b>Total</b>	<b>10.40%</b>	<b>9.94%</b>		<b>24.90%</b>	

## 2.2 Baseline Measure of TTBs Protection

We now describe the baseline measure of TTBs protection used in the empirical analysis. We convert data on new HS-6 product-level investigations into sectoral shares of imports subject to new investigations in each month. To avoid endogeneity concerns in the econometric analysis, we use previous-year import data to construct the weights. We consider the import coverage of TTBs to combine information on both extensive and intensive margin variation in import protection. In other words, the measure accounts for the fact that both the number of product lines under

investigation and the value of imports affected by TTBs change over time. Without correcting for the share of imports affected by TTBs, a case involving a single HS code which entails a large value of trade would be inappropriately measured as being “less important” than a case involving many HS codes with a modest amount of trade.

Let  $\mathcal{I}_{ijt}^k$  be a dummy variable equal to one if imports of product  $j$  from country  $k$  in industry  $i$  are subject to a new investigation at time  $t$ . We construct the following sectoral share of imports subject to new investigations in a given month:

$$\tau_{it} \equiv \sum_k \sum_j \omega_{ij}^k \mathcal{I}_{ijt}^k, \quad (1)$$

where  $\omega_{ij}^k$  is the previous-year, bilateral, sector- $i$  import share for product  $j$  from country  $k$ . As an example, consider the “Iron, Steel, and Ferro-Alloy” industry. In November 2000, the U.S. opened investigations on 27 imported products against 11 trading partners.<sup>11</sup> In this specific case, the imports covered by the investigations represented 3.7% of imports in the steel sector in the year 1999. This is our measure for November 2000.

Figure 2 plots time series data for  $\tau_{it}$  (measured on the left axis) and industry employment growth (measured on the right axis) for the four industries that feature the largest TTBs episodes (see Table 1).<sup>12</sup> Over time, the industry “Iron, Steel and Ferro-Alloy” features the largest variation in the share of imports subject to investigations. Across industries,  $\tau_{it}$  displays weak autocorrelation, averaging to 0.004. Similarly,  $\tau_{it}$  features weak correlation across industries. For instance, the average bilateral contemporaneous cross-correlation is equal to 0.045. Finally, the TTBs import-shares display some, albeit modest, countercyclicality with a few spikes occurring at times of negative employment growth.

To conclude, notice that while the use of previous-year weights in the construction of  $\tau_{it}$  removes endogeneity concerns in the econometric analysis, it potentially introduces measurement error. For this reason, in Section 6, we construct an alternative trade-policy measure that only considers the extensive margin of TTBs.

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<sup>11</sup>The trading partners were Argentina, China, India, Indonesia, Kazakhstan, Netherlands, Romania, South Africa, Taiwan, Thailand and Ukraine.

<sup>12</sup>See Appendix B for the remaining four other industries reported in Table 1.

## TTB Import Shares and Employment Growth

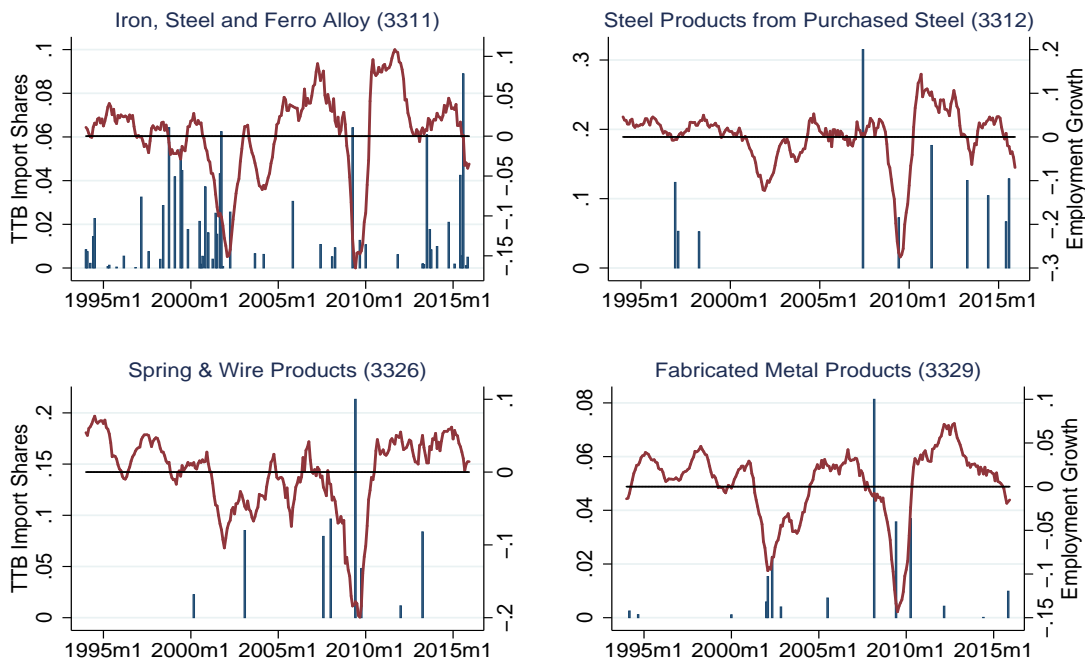


Figure 2. Share of imports affected by TTBs investigations in selected NAICS-4 industries (histograms) and employment growth (continuous line).

### 3 Identification of Trade-Policy Shocks

We estimate the effects of protectionism by computing impulse response functions from local projections. The methodology entails a two-stage estimation. In the first stage, we exploit institutional features of TTBs regulation to identify movements in import protection that are plausibly free of endogenous and anticipatory movements. In the second stage, we use the identified TTBs shocks to estimate the monthly response of industry employment following protectionism. We now describe in detail the identification of trade policy shocks and the measure of exposure to protectionism through vertical production linkages—“upstream protectionism” henceforth. In the next section, we discuss the local-projections approach.

#### 3.1 Identification Strategy

We adopt a consolidated identification strategy in the monetary policy literature, following the seminal work by [Romer and Romer \(2004\)](#). The idea is to purge the series of interest (TTBs protection,  $\tau_{it}$ , in our case) of movements taken in response to economic conditions that affect both

employment dynamics and the use of TTBs. Once this is accomplished, it is desirable to leave in as much of the remaining variation as possible. It is this variation that allows us to identify the effect of protectionism in the second stage of the empirical analysis. Our methodology differs from the typical approach in the trade literature, which exploits cross-sectional variation (e.g., treated versus untreated groups). The difference reflects the scope of the analysis and the nature of our data. While the trade literature typically focuses on long-run outcomes, we exploit high-frequency variation in trade policy instruments.

We use two alternative (and complementary) methods to purge the trade-policy measure of endogenous movements. One relies on within-industry time series variation in TTBs. The other uses the panel dimensions of the data, allowing us to include fixed effects that further control for unobserved heterogeneity across industries and over time.

The key question to address is what drives time-variation in  $\tau_{it}$ .<sup>13</sup> In theory, TTBs are intended for use only against unfair trade competition, although in practice there is latitude in the usage of contingent protection. For our purposes, what matters is distinguishing between investigations taken in response to cyclical economic conditions that affect industry employment relative to the remaining forces. In this perspective, part of the time-series variation in TTBs is plausibly exogenous, including responses to foreign predatory pricing and export subsidies, political pressure to affect the domestic market structure, and strategies to coordinate and support collusive behavior (Blonigen and Prusa, 2015). On the other hand, cyclical factors may also affect the use of TTBs. For instance, Bown and Crowley (2013) show that TTBs respond to previous macroeconomic conditions. Establishing causal inference requires controlling for the endogenous dynamics of  $\tau_{it}$ .

We take a broad view about the economic determinants of TTBs, considering the possibility that they respond to both industry-level and aggregate economic conditions. The institutional features of investigation procedures rule out simultaneity concerns (i.e., the possibility that  $\tau_{it}$  responds to current shocks). In particular, decision lags in the petitioning process (see Section 2) imply that, within a month, TTBs cannot respond to current shocks. We then control for past economic conditions by using lags of NAICS 4-digit employment growth as well as the lags of several macroeconomic variables.

While the nature of TTBs is backward looking—i.e., contingent protection addresses pre-existing

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<sup>13</sup>Cross-sectional variation in the use of TTBs is typically explained by import penetration, domestic industry employment conditions, and capital stock/intensity.

trade injury faced by import-competing producers—we also consider the possibility that demand for protection is forward-looking, i.e., the fact that industry producers may ask for protection when expecting a deterioration of economic conditions. First, we construct a benchmark measure for industry-level expected returns (the market-to-book ratio) and also consider macroeconomic forecast data. Second, when exploiting the panel dimension of the data, we include fixed effects that further absorb expected economic outcomes.

Finally, we identify trade policy shocks for the largest users of TTBs. We focus on the eight industries described in Table 1 where most of the variation in TTBs occurs. Intuitively, too few episodes in an industry (if any) pose econometric challenges that prevent consistent estimation. We now discuss the time-series and panel identification in detail.

### *3.1.1 Time-Series Approach*

We regress the trade policy measure  $\tau_{it}$  on both industry-level and aggregate controls. Industry controls include (i) lags of the growth rate of employment ( $\Delta L_{it}$ ) and (ii) the median market-to-book ratio ( $MB_{it}$ ). The latter is a widely used measure in the accounting and finance literature to proxy firms’ growth opportunities, capturing expected future economic conditions. Aggregate controls, summarized below by the vector  $\mathbf{x}_t$ , capture the effects of macroeconomic conditions on industry-level trade protection, also removing potential cross-sectional correlation in the identified trade-policy shocks. We include the growth rate of the real exchange rate, the growth rate of industrial production, the growth rate of real imports, and a benchmark measure of aggregate uncertainty, the VIX index. In addition, we include the quarterly median expected growth of aggregate industrial production (four quarters ahead) from the Survey of Professional Forecasters.

We relegate to Appendix A the details about the data. Here we briefly discuss the construction of the market-to-book ratio (Appendix A provides additional details). We use Compustat/Crsp firm-level data for each industry  $i$ , constructing the ratio between the market value of equity divided by the book value of equity. The market value is the total number of outstanding shares multiplied by the current share price (market capitalization). The book value is the accounting value calculated from the company’s balance sheet. A market-to-book ratio above 1 implies that investors are willing to pay more for a company than its net assets are worth, suggesting that the company has healthy future profit projections. Appendix B shows that a decrease (increase) in  $MB_{it}$  is typically followed by a decrease (increase) in industry employment ( $\Delta L_{it}$ ). A formal test of Granger causality confirms that the market-to-book ratio has forecasting power for industry employment growth. Hence, the



inclusion of  $MB_{it}$  controls for the possibility that expected employment outcomes drive demand for trade protection.

We estimate a fractional response model (Papke and Wooldridge, 1996, and Papke and Wooldridge, 2008), since the baseline trade policy measure is bounded between zero and one. Fractional response regressions are a popular tool to model continuous dependent variables, since they restrict the conditional mean to be between  $[0, 1]$ .<sup>14</sup> In addition, fractional response models capture potential non-linear relationships—e.g., when the outcome variable is near 0 or 1—a potential issue with a linear functional form for the conditional mean. Finally, notice that while the share of goods subject to TTBs  $\tau_{it}$  is equal to zero in several months, the zero values do not reflect selection bias (i.e., truncation or censoring).

We estimate the following model

$$\tau_{it} = G(\mu_{it}) + \varepsilon_{it}, \quad (2)$$

where  $\varepsilon_{it}$  is the prediction error. The conditional mean of  $\tau_{it}$  is defined by

$$G(\mu_{it}) \equiv \frac{\exp\{\mu_{it}\}}{1 + \exp\{\mu_{it}\}}.$$

In turn, the term  $\mu_{it}$  contains the following controls:

$$\mu_{it} \equiv \delta_i + \sum_{\kappa=1}^{p_\tau} \phi_{L_i}^\kappa \Delta L_{it-\kappa} + \sum_{\kappa=1}^{p_{MB}} \phi_{MB_i}^\kappa MB_{it-\kappa} + \sum_{\kappa=1}^{p_x} \Phi_{x_i}^\kappa \mathbf{x}_{t-\kappa}, \quad (3)$$

where  $\Phi_{x_i}^\kappa$  is a  $(p_x \times J)$  matrix of industry-specific coefficients, with  $J$  denoting the number of aggregate controls and  $p_x$  the number of lags. For parsimony, we do not include lags of the dependent variable given the absence of autocorrelation in the raw series for  $\tau_{it}$ —the autocorrelation function is never significantly different from zero across industries. In addition, we exclude time- $t$  controls, since the institutional features of TTBs imply that  $\tau_{it}$  cannot respond to current shocks within a month. The regressors satisfy the usual weak exogeneity assumption. We include twelve lags for the growth rate of employment, as well as three lags for the industry market-to-book ratio and the aggregate variables. In Section 6, we assess whether the non-linearity assumption in (2) matters for the results. We estimate by ordinary least squares (OLS) a distributed-lag model,

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<sup>14</sup>Empirical studies attempting to explain fractional responses have proliferated in recent years. Just a few examples include pension plan participation rates, industry market shares, television ratings, fraction of land area allocated to agriculture, and test pass rates.

obtaining similar results.

The estimated residuals from equation (2) are the identified TTBs shocks. As previously discussed, they represent changes in TTBs not taken in response to industry-specific and aggregate economic conditions, i.e., responses to foreign predatory pricing or subsidies, political pressure for protection not linked to cyclical factors, strategies to coordinate and support collusive behavior, just to name a few.

### 3.1.2 Panel Approach

We consider an alternative approach that exploits both cross-sectional and time-series variation in TTBs protection. The advantage of using the panel dimension of the data is the possibility of including industry and time fixed effects to control for unobserved heterogeneity and aggregate shocks, further addressing omitted-variables concerns. However, fixed effects potentially remove variation in  $\tau_{it}$  unrelated to economic conditions—the only part we would like to eliminate from the data. For this reason, the panel approach provides a more conservative strategy in the identification of exogenous variation in TTBs.

We consider the following panel, industry-level regression:

$$\tau_{it} = \chi + \sum_{\kappa=1}^{P\tau} \phi_{L_i}^{\kappa} \Delta L_{it-\kappa} + \sum_{\kappa=1}^{PMB} \phi_{MB_i}^{\kappa} MB_{it-\kappa} + \alpha_i + \eta_t + \varepsilon_{it}, \quad (4)$$

where  $\alpha_i$  denotes the industry fixed effect,  $\eta_t$  is the time  $t$  fixed effect, and  $\varepsilon_{it}$  is the industry-specific prediction-error term we want to estimate. The industry fixed effect controls for time-invariant inherent characteristics of a sector (e.g., volatility, tradability, skilled and unskilled labor intensity, etc.). The time fixed effect controls for all common aggregate shocks.

An issue when estimating the panel fixed-effect model is the violation of strict exogeneity of the regressors, e.g., the possibility that the fixed effect  $\alpha_i$  is correlated with industry controls. For instance, with a small  $T$ , both OLS and the within-group estimator yield inconsistent estimates.<sup>15</sup> In our context, the long time dimension of the panel (“large  $T$ ”) substantially mitigates such concern, as the bias decreases asymptotically with  $T$ . This is confirmed by the fact that we obtain very similar results when estimating (4) by OLS, in first difference, or using the within-group estimator. The results presented below are for the within-group estimator.

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<sup>15</sup>OLS suffer from an omitted variable bias, since  $\alpha_i$  is part of the error term  $\varepsilon_{it}$ . The within-group estimator induces correlation between the regressors and the error term when demeaning the data (Nickell, 1981)

### Predicted vs. Actual TTB Import Shares



Figure 3. Share of imports affected by antidumping investigations in selected NAICS-4 industries (blue histograms) and predicted values from the fractional-response model (red histograms).

## 3.2 Results

Figure 3 plots the predicted values from the fractional-response model against the data. For each industry, the difference between each observation and the corresponding predicted-value represents the estimated shock in a month. The figure conveys two main insights. First, the regression in (2) explains a significant portion of various spikes in TTBs across industries, in particular in the second part of the 2000s. This implies that not all the spikes in TTBs investigations observed in the data can be treated as exogenous. Second, there remains unexplained variation in TTBs variation in various episodes. As shown by Table 3, the pseudo- $R^2$  of the time-series regressions in (2) is between 10% and 41% across industries.

The trade-policy shocks identified with the panel approach in (4) are positively correlated with the shocks identified using the fractional-response model. For the sector “Iron, Steel and Ferro Alloy”—the largest users of TTBs in our sample—the correlation is 0.80, while on average it is 0.43. The  $R^2$  of the panel specification is 18%.

Regardless of the econometric model we consider (time-series or panel), the identified trade-

Table 3: First-Stage Estimation

Identification Approach	Statistics	NAICS-4 Industry Code							
		3311	3251	3329	3312	3326	3252	3314	3331
Time Series (Fractional Logit)	Pseudo R-squared	0.10	0.10	0.35	0.34	0.46	0.34	0.41	0.41
	Industry Ljung-Box Test (p-value)	0.06	0.77	0.47	0.85	0.70	0.14	1.00	0.96
	Joint Ljung-Box Test (p-value)	0.68							
Panel	R-squared	0.18							
	Industry Ljung-Box Test (p-value)	0.17	0.97	0.14	0.99		0.86	0.93	0.25
	Joint Ljung-Box Test (p-value)	0.16							

policy shocks also have plausible statistical properties, i.e., they are serially uncorrelated and not correlated across industries. To provide a formal assessment, we run a Ljung-Box test on each industry-specific estimated residual,  $\hat{\epsilon}_{it}$ , as well as a multivariate Ljung-Box test. The null hypothesis is lack of serial autocorrelation and lack of contemporaneous cross-correlation, respectively. As shown in Table 3, the tests cannot reject the null hypotheses at the 5% significance level.<sup>16</sup>

In Appendix C, we present the coefficient estimates for the fractional-response model and the panel regression. Various lags of the growth rate of employment are negative and statistically significant. In contrast, despite having forecasting power for employment growth, lags of the market-to-book ratio are statistically different from zero only in three industries.

### 3.3 Measuring Upstream Protectionism

We now turn to the construction of the industry-specific measure of upstream protectionism. Our approach follows the trade literature that studies the long-run effects of input tariffs. For instance, [Amiti and Konings \(2007\)](#) compute input tariffs as a weighted average of the output tariffs for each industry, where the weights are the cost shares of each input-industry in a base year. We combine the identified structural TTBs shocks with information from input-output matrices on the extent to which sectors use each others' output as an intermediate input. For a given industry  $i$ , we construct a weighted average of the identified structural shocks across industries, excluding the industry  $i$ :

$$\hat{\epsilon}_{it}^{IO} \equiv \sum_{j \neq i} \theta_{ij} \hat{\epsilon}_{jt}, \quad (5)$$

<sup>16</sup>As is common practice in the time series literature, we consider 12 lags when performing the test.

where the fixed weight  $\theta_{ij}$  reflects the contribution of sector  $j$  to the output of industry  $i$ .<sup>17</sup> The definition of  $\hat{\varepsilon}_{it}^{IO}$  implies that an increase in protectionism in industry  $j$  is more important for industry  $i$  when the input share of sector  $j$  in sector  $i$  is higher. We compute each weight  $\theta_{ij}$  using the total-requirements input-output table. As discussed in Section 2, we construct the table using the 2007 direct-requirements table. The use of fixed weights has the advantage of removing endogeneity concerns in the construction of  $\hat{\varepsilon}_{it}^{IO}$  (at the cost of potentially introducing measurement error).

#### 4 The Industry-Level Effects of Protectionism

We now study the effects of protectionism on industry outcomes, as well as the effects of protectionism through vertical production linkages. We estimate impulse response functions (IRFs) using [Jorda \(2005\)](#)'s local projection method. Local projections have become a popular and well-established tool to estimate IRFs in macroeconomics, and a growing number of studies applies this methodology with panel data (e.g., [Auerbach and Gorodnichenko, 2013](#), [Jorda and Taylor, 2016](#), [Leduc and Wilson, 2013](#), and [Ottonello and Winberry, 2018](#) just to name a few). The approach consists in running a sequence of predictive regressions of a variable of interest on a structural shock for different prediction horizons. The IRFs correspond to the sequence of regression coefficients of the structural shock of interest. A key advantage [Jorda \(2005\)](#)'s method is that IRFs are estimated directly, without imposing (potentially inappropriate) dynamic restrictions, i.e., without specifying or estimating the unknown true multivariate dynamic process. [Jorda \(2005\)](#) shows that local projections are robust to a misspecification of the data generating process, they can accommodate nonlinearities, and they can be estimated in a simple univariate framework.

In our context, the structural shocks of interest are the identified exogenous movements in industry-level TTBs. First, we focus on employment outcomes in industries that impose import protection. Second, we estimate the effects of protectionism through input-output linkages, i.e., we estimate the response of downstream-industry employment following protection in upstream industries.

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<sup>17</sup>When aggregating the sectoral shocks,  $\hat{\varepsilon}_{i,t}^{IO}$  ignores that  $\hat{\varepsilon}_{j,t}$  are sectoral trade-share residuals. As discussed in Section 6, our results are robust to expressing each  $\hat{\varepsilon}_{j,t}$  as a share of aggregate imports.

#### 4.1 The Effects of TTBs in Protected Industries

Let  $\Delta L_{it+h} \equiv \log L_{it+h} - \log L_{it-1}$  denote the cumulative NAICS 4-digit employment difference between time  $t$  and time  $t+h$ . Continue to denote with  $\hat{\epsilon}_{i,t}$  the trade-policy shocks in sector  $i$  identified in the first stage (either with the fractional-response model or the panel specification). We estimate the following set of  $h$ -steps ahead predictive panel regressions, for  $h = 0, \dots, H$ :

$$\Delta L_{it+h} = \delta^h + \gamma_h \hat{\epsilon}_{it} + \psi_{t+h} + \nu_{ih}^{N4} + \epsilon_{it+h}, \quad (6)$$

where  $\nu_{ih}^{N4}$  denotes a NAICS 4-digit industry fixed effect in the cumulative employment growth between time  $t-1$  and  $t+h$ , the term  $\psi_{t+h}$  is a time fixed effects, and  $\epsilon_{it+h}$  is the prediction error term. The industry fixed effect captures industry-specific trends in employment between time  $t-1$  and  $t+h$ . Controlling for specific industry time trends is important, as industries that are growing slower than others could systematically receive higher-than-forecasted trade protection and hence persistent shocks. Thus, industry-specific shocks could be correlated with industry-specific trends, and omitting such trends could lead to a bias on the impulse response coefficients. The time-fixed effect captures common shocks across industries. The coefficient  $\gamma_h$  gives the response of the cumulative employment difference at time  $t+h$  following a shock at time  $t$ . Thus, the local projections correspond to the set of coefficients  $\gamma_h$  for  $h = 0, \dots, H$ .

A few observations are in order. First, following standard practice in the literature, we consider the cumulative employment difference,  $\Delta L_{it+h}$ , to control for persistence in  $L_{it}$  while alleviating issues of correlation between the error term and regressors that are potentially introduced by fixed effects in dynamic panel regressions. Second, we do not include time-varying, industry-level controls, since they are already used in the first-stage estimation, i.e., such controls are orthogonal to  $\hat{\epsilon}_{it}$ . Third, we compute bootstrapped, clustered confidence intervals for each impulse response estimate ( $\gamma_h$ ), accounting for the fact that  $\hat{\epsilon}_{it}$  is a generated regressor.<sup>18</sup>

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<sup>18</sup>We conduct wild-bootstrap tests of the linear hypothesis  $\gamma_h = 0$  for each  $h = 0, \dots, H$ . We consider 1000 replications and cluster both standard errors and bootstrap by NAICS 4-digit industries.

## 4.2 The Role of Production Networks

In order to estimate the effects of protectionism through production networks, we run the following set of  $h$ -steps ahead predictive panel regressions:

$$\Delta L_{it+h} = \delta^h + \gamma_h^{IO} \hat{\epsilon}_{it}^{IO} + \psi_{t+h} + \nu_{ih}^{N4} + \epsilon_{it+h}. \quad (7)$$

As in equation (6), we include both industry and time fixed effects. The dynamic multipliers of interest are  $\gamma_h^{IO}$  for  $h = 0, \dots, H$ . Consistent with the literature that studies trade liberalization episodes, equation (7) estimates the average within-industry effect of average upstream protectionism. We include all the manufacturing industries in the sample when estimating equation (7).

## 4.3 Results

Figure 4 plots the impulse responses using the trade-policy shocks identified with the time-series regressions in (2). The top panel plots the average response of employment in protected industries following an exogenous increase in TTBs. The continuous line is the point estimate of each  $\gamma_h$ , while the grey area plots the 90% bootstrapped confidence interval.

We consider a positive innovation equal to 2 percentage points, corresponding to the average share of imports subject to new TTBs in the industries reported in Table 1. The point estimate of the employment response is positive for approximately two years, and then it turns negative. The response is never statistically significant.

Alternative possible explanations exist for the lack of significant employment effects in protected industries. First, domestic producers may experience profit gains from TTBs, without necessarily boosting production. This is consistent with the idea that import protection changes the pricing behavior of domestic producers by shielding them from foreign competition and enabling them to raise markups (e.g., [Amiti, Redding, and Weinstein, 2019](#)). Second, as discussed in [Barattieri, Cacciatore, and Ghironi \(2018\)](#), trade protection triggers both expenditure switching and expenditure changing, which are offsetting forces. Expenditure switching reflects higher output demand in protected industries. Expenditure changing reflects lower domestic demand due to overall higher prices (as long as foreign and domestic products are not perfectly substitutable). Third, there could be heterogenous responses across producers within a protected industry, including a different exposure to products covered by TTBs.

The picture is different when looking at the downstream effects of protectionism. The bottom



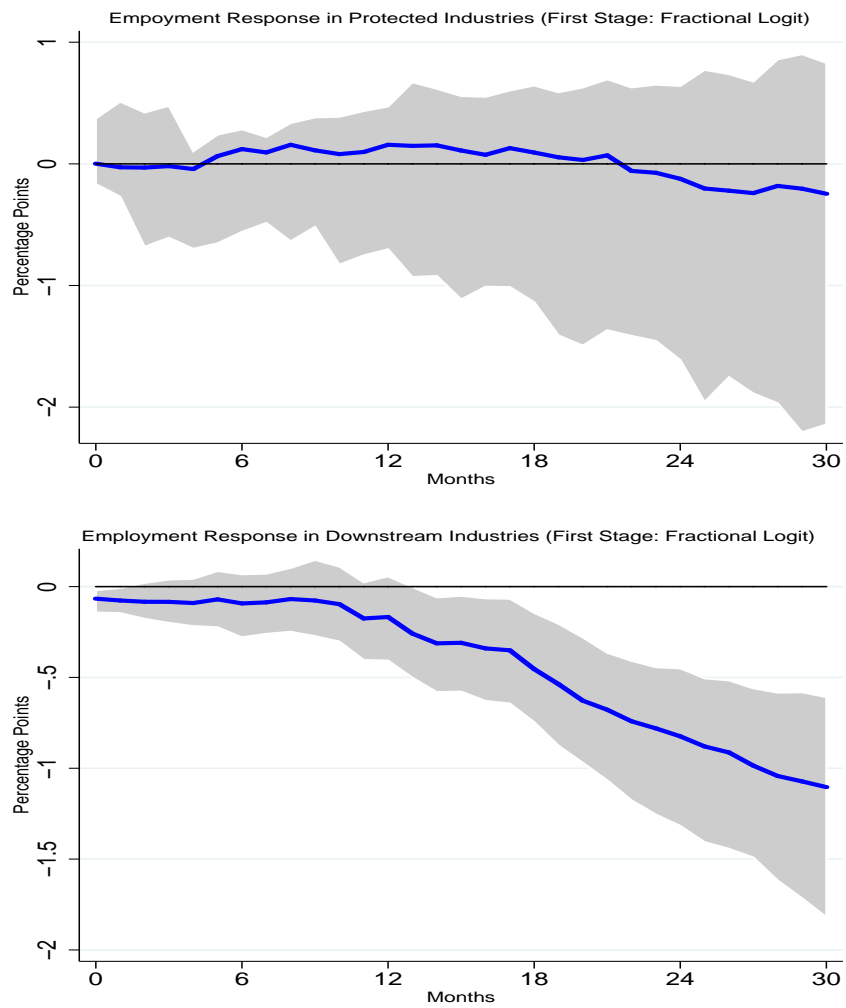


Figure 4. Impulse responses following a protectionism shock. *Top panel:* Average employment response in protected industries. *Bottom panel:* Average downstream-industry employment response. First-stage: Fractional-response model.

panel in Figure 4 plots the employment response following protectionism in upstream industries. For illustrative purposes, we consider again a 2 percentage points increase in the share of imports subject to investigation in all upstream industries, weighting each upstream shock using the average input-output coefficient. That is, we set  $\varepsilon_{it}^{IO} \equiv 0.02 \sum_j \bar{\theta}_j$ , where  $\bar{\theta}_j = [1/(N-1)] \sum_{j \neq i} \theta_{ij}$ . Protectionism triggers statistically significant, negative effects on average downstream-industry employment. In particular, a uniform 2 percentage-points increase in the share of imports subject to protectionism reduces downstream employment approximately by 0.8 percentage points after 2 years.

Figure 5 plots the impulse responses using the trade-policy shocks identified with the panel regression (4). The main message is largely unaffected. Protectionism does not trigger a statistically significant increase in industry employment, and it leads to a decline in employment in downstream industries. The magnitude of the negative effects on downstream employment is somewhat smaller, although the response remains statistically significant at all horizons.

The persistent response of downstream employment is consistent with the fact that TTBs duties are remarkably sizable (see again Table 1) and long-lasting (they remain in place for 5 years and they are potentially renewable).

## 5 Inspecting The Mechanism

In this section, we explore the mechanism behind the negative response of downstream employment. First, we show that a significant increase in producer prices following upstream protectionism precedes the employment decline. Second, we show that employment losses are on average higher in industries where demand is more price elastic.

### 5.1 Prices

There exist alternative possible explanations for the negative effects of protectionism on employment in downstream industries. For instance, when an intermediate input is subject to TTBs, downstream producers may find it hard to quickly replace it, ending up paying a higher price. Alternatively, producers may switch to potentially less-efficient domestic suppliers, facing higher prices relative to the pre-TTBs scenario. While these two scenarios have different implications for the response of imports, marginal costs and final-producer prices in downstream industries are predicted to increase in both cases. In turn, higher prices would reduce competitiveness, lowering

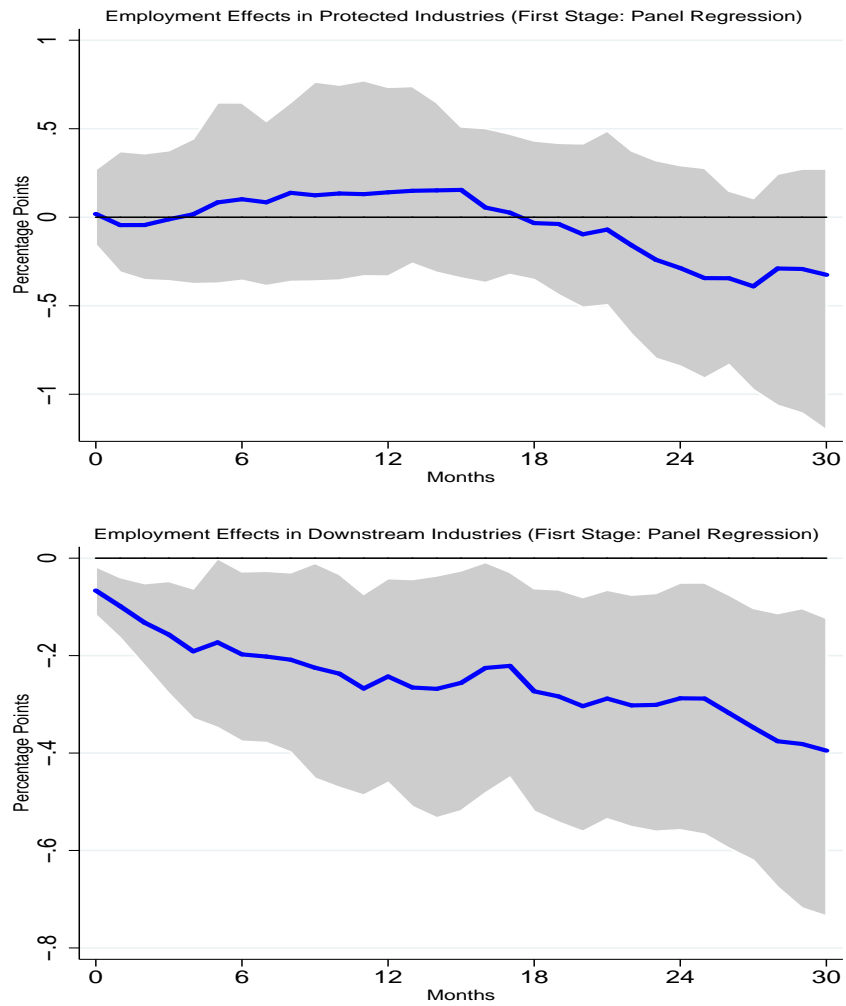


Figure 5. Impulse responses following a protectionism shock. *Top panel:* Average employment response in protected industries. *Bottom panel:* Average downstream-industry employment response. First-stage: Panel regression.

demand and employment.

In light of these considerations, we investigate the response of intermediate-input and final-producer prices in downstream industries. We use Producer Price Index (PPI) data for NAICS 4-digit industries from the Bureau of Labor Statistics. The data are available at monthly frequency starting from 2004. For each industry  $i$ , we construct an intermediate-input price index  $P_{it}^I$  as a weighted average of producer prices in upstream industries (i.e., industries whose output is used as an input in industry  $i$ ):

$$P_{it}^I \equiv \sum_{j \neq i} \theta_{ij} P_{jt},$$

where  $P_{jt}$  is the PPI index in industry  $j$  at time  $t$ . As in Section 3, we use fixed weights from I-O tables that reflect the contribution of each sector  $j$  to the output of industry  $i$ .

Let  $\Delta P_{it+h} \equiv \log P_{it+h} - \log P_{it-1}$  and  $\Delta P_{it+h}^I \equiv \log P_{it+h}^I - \log P_{it-1}^I$  denote, respectively, the cumulative growth rate of final and intermediate-input prices between time  $t-1$  and  $t+h$ . We estimate the response of final producer prices by running the following set of  $h$ -steps ahead predictive panel regressions:

$$\Delta P_{it+h} = \delta^h + \pi_h \hat{\epsilon}_{it}^{IO} + \psi_{t+h} + \nu_{ih}^{N4} + \epsilon_{it+h}, \quad (8)$$

where  $\hat{\epsilon}_{it}^{IO}$  is estimated using the fractional-response model in (2) and  $h = 0, \dots, H$ . The coefficient  $\pi_h$  gives the response of final prices at time  $t+h$  following a trade-policy shock at time  $t$ . The local projections correspond to the set of coefficients  $\pi_h$  for  $h = 0, \dots, H$ . Similarly, we estimate the response of intermediate-input producer prices:

$$\Delta P_{it+h}^I = \delta^h + \pi_h^I \hat{\epsilon}_{it}^{IO} + \psi_{t+h} + \nu_{ih}^{N4} + \epsilon_{it+h}. \quad (9)$$

In this case, the coefficient  $\pi_h^I$  gives the response of intermediate-input prices at time  $t+h$  following a trade-policy shock at time  $t$ .

Panel A in Figure 6 shows the response of final-producer prices, while Panel B reports the response of intermediate-input prices. As before, we consider a uniform increase of 2 percentage points in the share of imports subject to TTBs. In both cases, prices increase slowly, peaking approximately 18 months after the shock. The increase is statistically significant and economically sizeable. Final-producer prices increase by approximately 0.6 percentage points at the peak. Intermediate-input prices increase by approximately 1 percentage point. From a timing perspec-

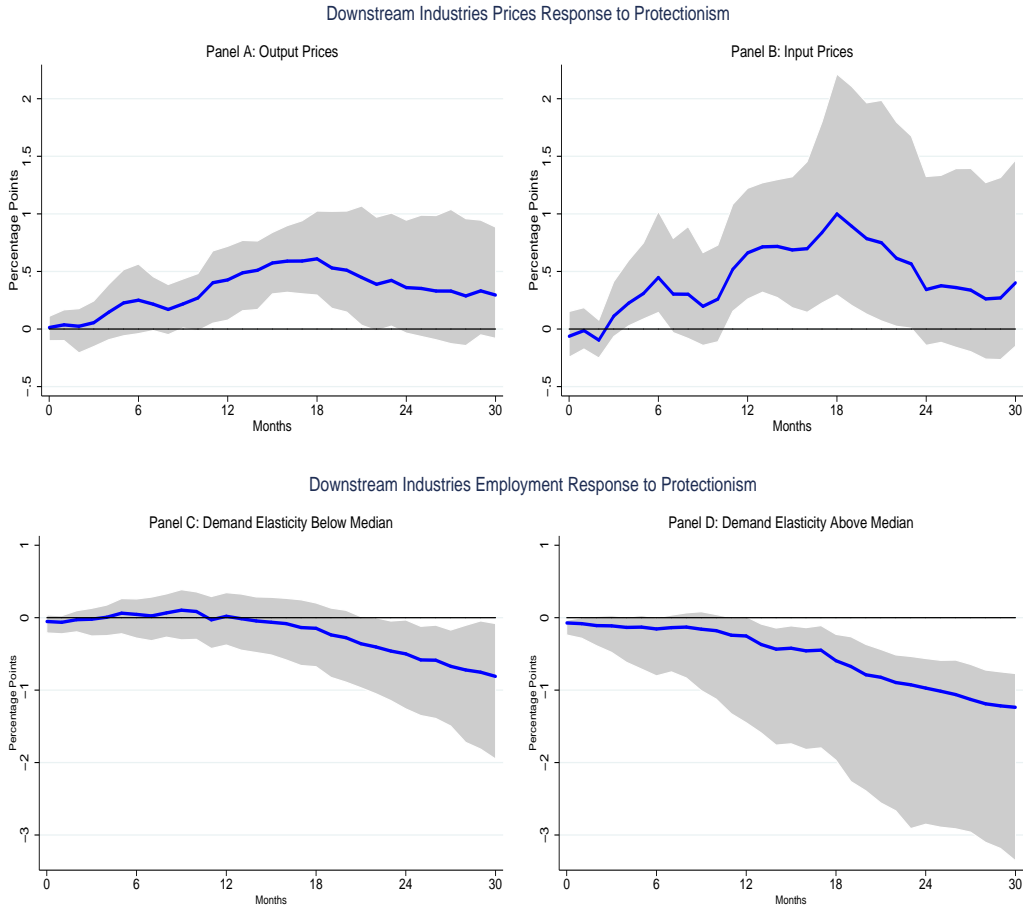


Figure 6. Impulse responses following protectionism in sourcing industries. *Panel A*: Producer-price response in downstream industries. *Panel B*: Intermediate-input price response in downstream industries. *Panel C*: Downstream-employment response in industries where the elasticity of substitution is below the median. *Panel D*: Downstream-employment response in industries where the elasticity of substitution is above the median. First-stage: Fractional-response model.

tive, the increase in prices precede the decline in employment (see Figure 4), suggesting there is a loss of competitiveness in downstream industries that causes the employment decline.

## 5.2 Employment and Demand Elasticity

To conclude, we explore whether the strength of the price channel discussed above depends on the price elasticity of demand. In particular, we test whether the employment decline is stronger in industries where product differentiation is lower (i.e., when goods substitutability is higher).

We use data from [Broda and Weinstein \(2006\)](#) who estimate elasticities of substitution among products at various levels of aggregation. For the latest period of their sample (1990-2001), the

estimates are available at the HS 10-digit level.<sup>19</sup> We use again the [Pierce and Schott \(2009\)](#) conversion table to obtain elasticities at the NAICS 4-digit industry level. First, we assign each HS 10-digit product to the corresponding NAICS 4-digit industry. Then we compute the median elasticity of substitution of the products that belong to each industry.

We amend the baseline local projection in (6) to include information on goods substitutability. In particular, we consider the following set of panel regressions at horizons  $h = 0, \dots, H$ :

$$\Delta L_{it+h} = \delta^h + \mathcal{I} \gamma_h^{IO,H} \hat{\varepsilon}_{it}^{IO} + (1 - \mathcal{I}) \gamma_h^{IO,L} \hat{\varepsilon}_{it}^{IO} + \psi_{t+h} + \nu_{ih}^{N4} + \epsilon_{it+h}, \quad (10)$$

where  $\mathcal{I}$  is a dummy variable equal to one if the elasticity of substitution in industry  $i$  is above the sample median, and zero otherwise. Therefore, the coefficient  $\gamma_h^{IO,H}$  ( $\gamma_h^{IO,L}$ ) gives the response of employment growth at time  $t + h$  following a trade-policy shock at time  $t$  in industries where products feature an elasticity of substitution above (below) the sample median.

Panel C and D in Figure 6 show that industries where products have on average a higher elasticity of substitution (right panel) feature a larger and more persistent employment decline relative to industries whose products feature on average a lower elasticity (left panel). Thus, a given increase in input costs (upstream protectionism) that makes domestic producers less competitive (i.e., higher marginal costs and prices), leads to a larger employment decline in industries that sell relatively more substitutable goods.

## 6 Robustness

We assess the robustness of our findings with respect to several dimensions. We consider alternative approaches to estimate the trade policy shocks,  $\hat{\varepsilon}_{it}$ , a different methodology to measure upstream protectionism,  $\hat{\varepsilon}_{it}^{IO}$ , and alternative measures of protectionism.

### 6.1 Trade-Policy Shocks Identification

#### 6.1.1 *Distributed-Lag Model*

We first consider a linear model for the conditional mean of the trade-policy variable in the time-series identification. In particular, we replace the fractional-response model with a linear distributed-lag model:  $\tau_{it} = \mu_{it} + \varepsilon_{it}$ , where  $\mu_{it}$  is still defined by (3). While in principle ordinary

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<sup>19</sup>The data are available at <http://www.columbia.edu/~dew35/TradeElasticities/TradeElasticities.html>.

least squares may render predicted values outside the feasible range, Panel A in Figure 7 shows that the employment impulse responses are not substantially different from Figure 4.

### 6.1.2 Probit Model

A second concern is measurement error due to the use of lagged imports data when constructing the share of imports subject to protection ( $\tau_{it}$ ). To address this issue, we consider an alternative econometric model that only uses the extensive-margin variation in TTBs. For each industry, we estimate the residuals from a probit model where the dependent variable is equal to one when there is at least one investigation in a given month (and zero otherwise):

$$\tau_{it} \equiv \begin{cases} 1 & \text{if at least one HS-6 code is subject to a new AD investigation in industry } i \\ 0 & \text{otherwise} \end{cases}.$$

Modeling the probability of an investigation avoids the econometric difficulties posed by the count nature of the raw measure of TTBs investigations.<sup>20</sup> Panel B in Figure 7 plots the local projection estimates using the probit model in the first stage of the estimation. We assume a unitary increase in both  $\hat{\varepsilon}_{it}$  and  $\hat{\varepsilon}_{it}^{IO}$ . Qualitatively, the results are very similar to our baseline estimates. Quantitatively there are obvious differences, since now a unitary increase in  $\hat{\varepsilon}_{it}$  corresponds to a change in the probability of protectionism from zero to one in a given industry.

## 6.2 Alternative Measure of Upstream Protectionism

Our benchmark measure of upstream protectionism,  $\hat{\varepsilon}_{it}^{IO} \equiv \sum_{j \neq i} \theta_{ij} \hat{\varepsilon}_{jt}$ , exploits the contribution of each sector  $j$  to output of industry  $i$ . However,  $\hat{\varepsilon}_{it}^{IO}$  does not consider that upstream shocks ( $\hat{\varepsilon}_{jt}$ ) are sectoral import shares. An alternative is to express the sectoral-trade shocks as a fraction of a common quantity (total imports):

$$\hat{\varepsilon}_{it}^{IO} \equiv \sum_{j \neq i} \theta_{ij} s_j \hat{\varepsilon}_{jt},$$

where  $s_j$  is the previous-year import share of sector  $j$  relative to aggregate imports. Panel C in Figure 7 shows that the results remain similar to the benchmark specification. Also in this case we consider a uniform 2-percentage-points increase in upstream protectionism:  $\hat{\varepsilon}_{it}^{IO} \equiv 0.02 \sum_j \bar{\theta}_j$ , where  $\bar{\theta}_j = [1/(N-1)] \sum_{j \neq i} \theta_{ij} s_j$ .

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<sup>20</sup>The original count measure would require a discrete-choice model, which constraints more severely the estimation with time series data.



## Employment Response to Protectionism

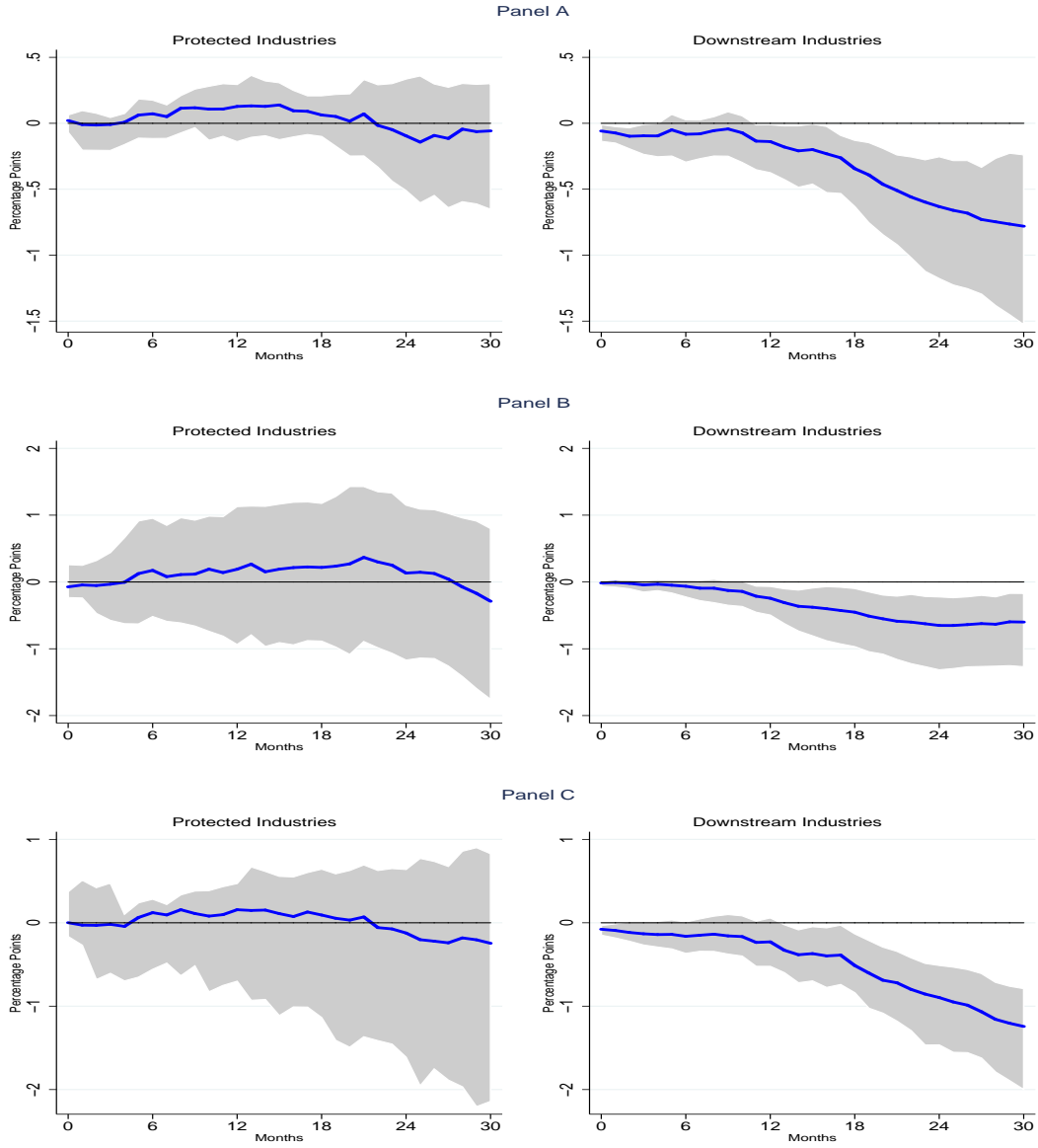


Figure 7. Impulse responses following a protectionism shock. *Panel A*: Distributed-lag model in the first-stage estimation. *Panel B*: Probit model in the first-stage estimation. *Panel C*:  $\hat{\varepsilon}_{it}^{IO}$  constructed with aggregate import weights.

## Employment Response to Protectionism

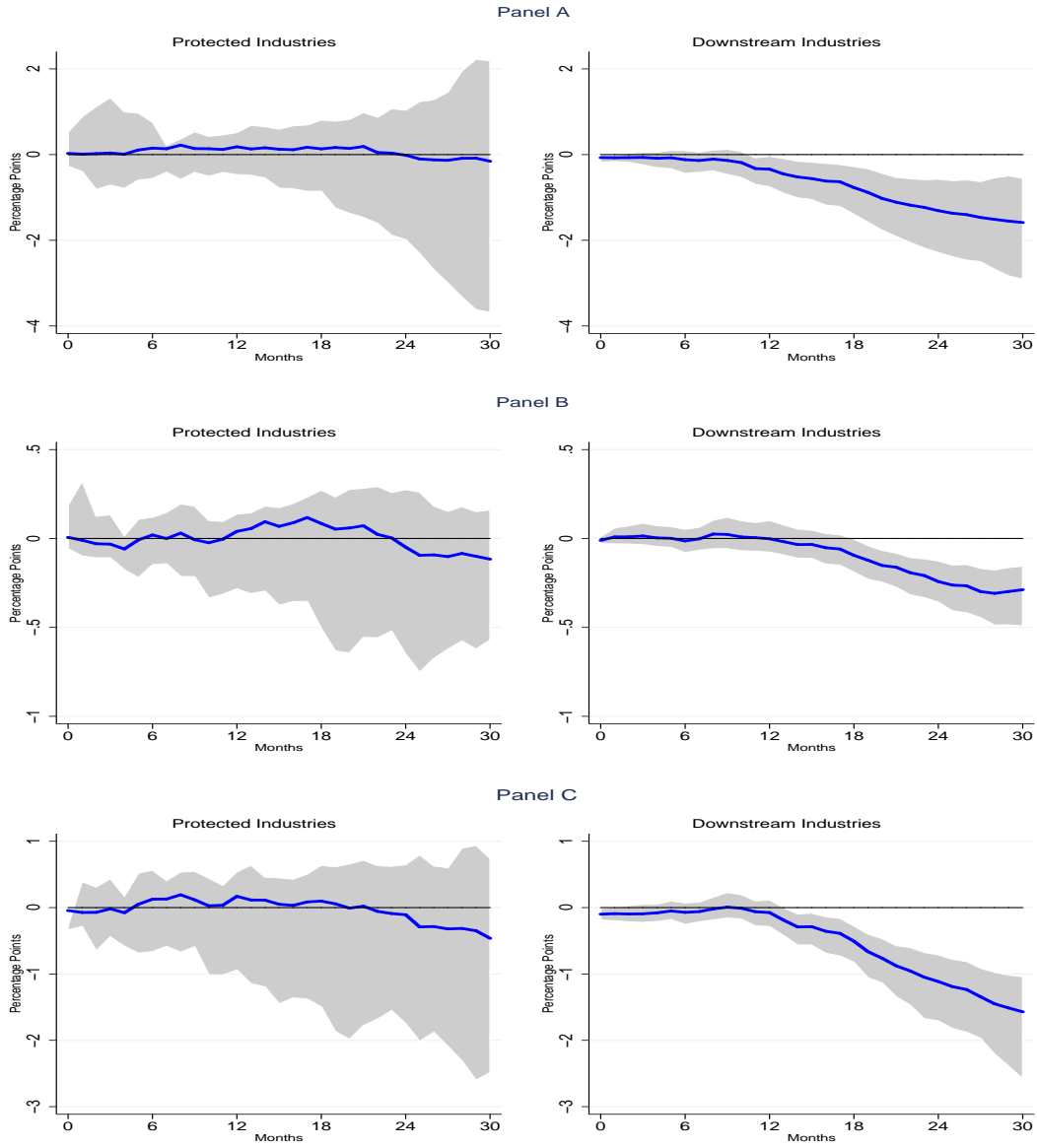


Figure 8. Impulse responses following a protectionism shock. *Panel A*: Average import shares when constructing  $\tau_{it}$ . *Panel B*: TTBs include global safeguards. *Panel C*: Only episodes that end up with tariffs.

## 6.3 Alternative Measures of Protectionism

### 6.3.1 Average Trade Shares

We construct the baseline trade-policy measure  $\tau_{it}$  using previous-year import shares. An alternative possibility is to consider average import shares over the whole sample. In this case, we compute:

$$\tau_{it} \equiv \sum_k \sum_j \bar{\omega}_{ij}^k \mathcal{I}_{ijt}^k,$$

where  $\bar{\omega}_{ij}^k$  denotes the average, bilateral, sectoral import share for each product under investigation. As shown by Panel A in Figure 8, the results are not substantially affected by the different weights.

### 6.3.2 Global Safeguards

In the baseline specification, we exclude global safeguards from TTBs. Panel B in Figure 8 shows that, qualitatively, the results are not affected by their inclusion. Quantitatively, magnitudes are somewhat smaller, driven by a large outlier in the “Iron, Steel and Ferro-Alloy.”

### 6.3.3 Only Successful Investigations

Finally, we restrict the sample by considering only investigations that end up with the imposition of tariffs. This allows us to test whether the results are driven by investigations that ultimately did not lead to trade protection. Panel C in Figure 8 shows that the results are robust to this alternative choice.

## 7 Conclusions

We used high frequency data on U.S. temporary trade barriers to estimate the effects of protectionism on economic activity in protected industries and through input-output linkages. We found that protectionism has small, short-lived, and mostly insignificant beneficial effects in protected industries. In contrast, protectionism has long-lasting and significant negative effects in downstream industries. The employment decline follows an increase in the price of intermediate inputs and final goods. Thus, loss of competitiveness is a candidate explanation for the negative response of employment through production networks. Employment losses are stronger in industries characterized by higher goods substitutability.

Our results suggest avenues for future research. First, considering firm-level data would allow to uncover potential heterogeneity in the effects of protectionism. Second, it would be important to analyze the aggregate implications of TTBs through production networks.

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# Technical Appendix

## A Data

We use seasonally-adjusted data for industry employment from the Current Employment Statistics from the Bureau of Economic Analysis.<sup>21</sup> Aggregate data for imports, industrial production, and the effective real exchange rate (all seasonally-adjusted) are from the Federal Reserve Economic Data. We use the following series: XTIMVA01USM667S, INDPRO, and RBUSBIS. Data on the median forecast of industrial production come from the Survey of Professional Forecasters. We use the series *dindprod6*.<sup>22</sup> The trade data used to construct the weights in (1) are bilateral HS 6-digit annual level of imports from Comtrade (downloaded through Wits). Finally, monthly producer-price data correspond to the Producer Price Index PC from the U.S. Bureau of Labor Statistics.<sup>23</sup>

We now turn to the construction of the median, industry-level market-to-book ratio. Following standard practice in the finance literature, we first construct the market-to-book ratio at firm level by merging data from Compustat and Crsp, a panel of publicly listed U.S. firms. The market-to-book is the market value of a firm's equity divided by the book value of equity. The market value corresponds to the average monthly price of a share (the variable *prc* in Crsp) times the amount of outstanding shares (*shrout* in Crsp). The book value is the sum of stockholders' equity plus deferred-tax and investment-tax credit (*txditcqin* in Compustat) minus the book value of preferred shares (*pstkq* in Compustat). We measure stockholders' equity by shareholders' equity (*seqq* in Compustat).<sup>24</sup> We convert SIC 4-digit firms' codes to NAICS 6-digit codes using the yearly conversion tables from [Pierce and Schott \(2009\)](#).<sup>25</sup> We then aggregate to NAICS 4-digit and construct the median market-to-book ratio for each industry.

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<sup>21</sup>The data are available at <https://download.bls.gov/pub/time.series/ce/>.

<sup>22</sup>The series is available at <https://www.philadelphiafed.org/research-and-data/real-time-center>.

<sup>23</sup>The series is available at: <https://download.bls.gov/pub/time.series/pc/pc.txt>.

<sup>24</sup>When the measure is not available, as is common practice in the literature, we use common equity plus par value of preferred shares (*ceqq + pstkq*), or (when also the latter is not available) total asset minus total liability (*atq - ltq*).

<sup>25</sup>When the concordance is missing, we rely on the 2002 concordance table from the Census Bureau (available at <https://www.census.gov/eos/www/naics/concordances/concordances.html>).



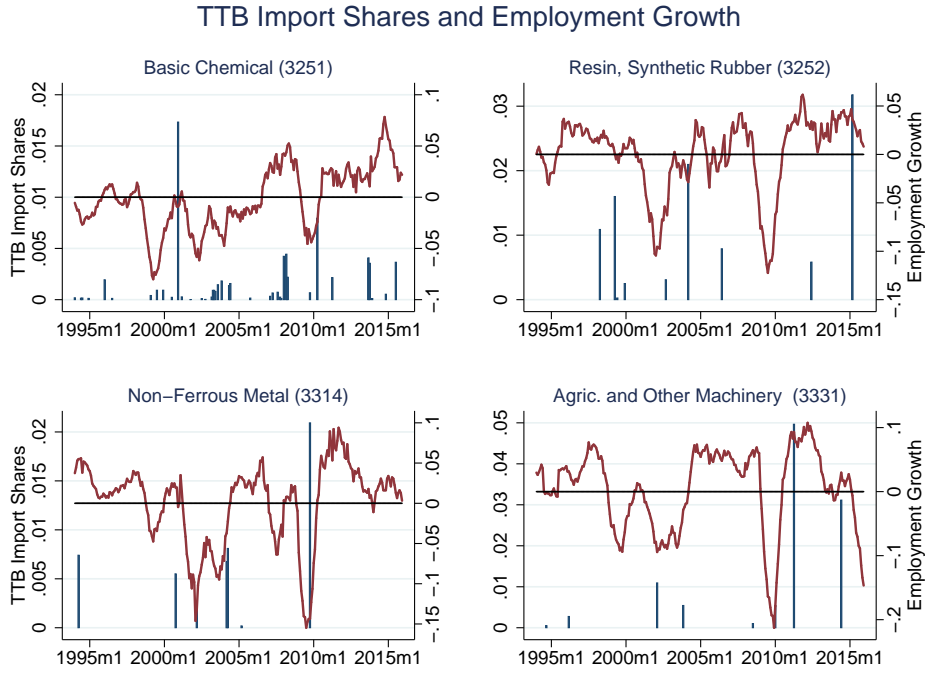


Figure A.1. Share of imports affected by TTBs investigations in selected NAICS-4 industries (histograms) and employment growth (continuous line).

## B Other Descriptive Statistics

### B.1 Share of Imports Subject to TTBs and Employment Growth

Figure A.1 plots time series data for  $\tau_{it}$  (measured on the left axis) and industry employment growth (measured on the right axis) for the industries appearing in Table 1 that are not plotted in the main text.

### B.2 Market-to-Book Ratio

Figure A.2 and A.3 plot the evolution of the market-to-book ratio and employment growth for the industries that are the largest users of TTBs. The figure shows that movements in  $MB_{it}$  lead movements in  $\Delta L_{it}$ . A formal test of Granger causality confirms that the market-to-book ratio has forecasting power for employment growth (see Table A.1). We test whether the market-to-book ratio provides statistically significant information about future employment-growth values. For

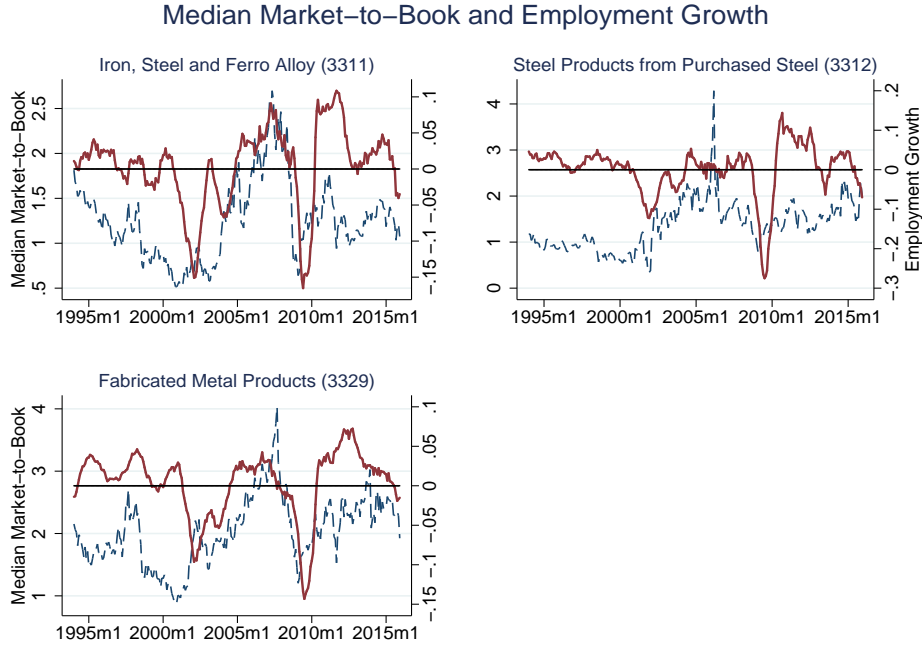


Figure A.2. Market-to-book ratio in selected NAICS-4 industries (dashed line) and employment growth (continuous line).

each industry, we regress employment growth on three lags of the ratio together with twelve lags of the dependent variable.

### C First-Stage Regression Output

Table A.2 reports the coefficients estimates from the first-stage estimation for both the fractional-response model and the panel specification. For the fractional-response model, we report average marginal effects. They represent the average increase (decrease) in the predicted share of sectoral imports subject to TTBs following a unitary increase in the regressors

Figure A.4 plots the predicted values from the fractional-response model against the data for the industries appearing in Table 1 that are not plotted in the main text.

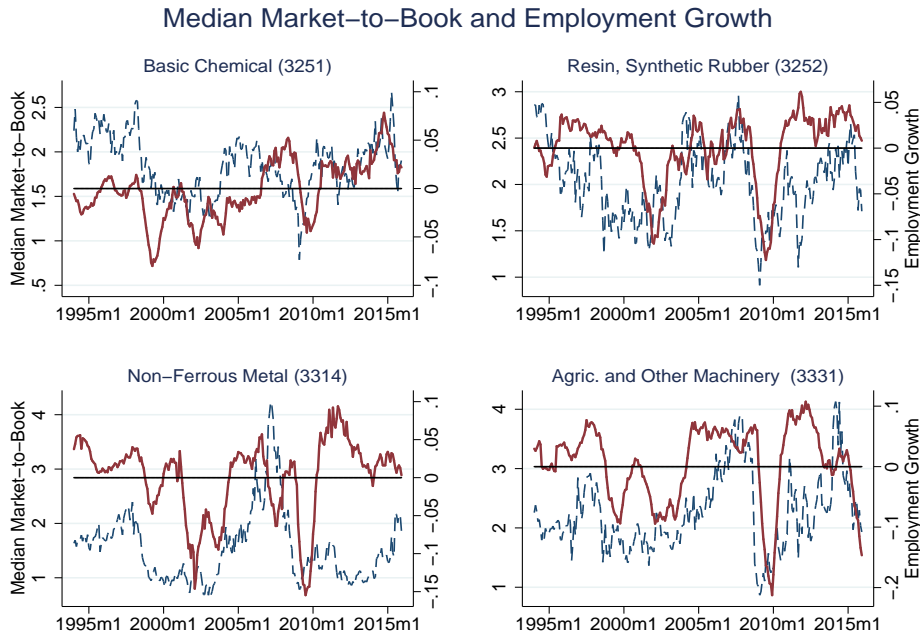


Figure A.3. Market-to-book ratio in selected NAICS-4 industries (dashed line) and employment growth (continuous line).

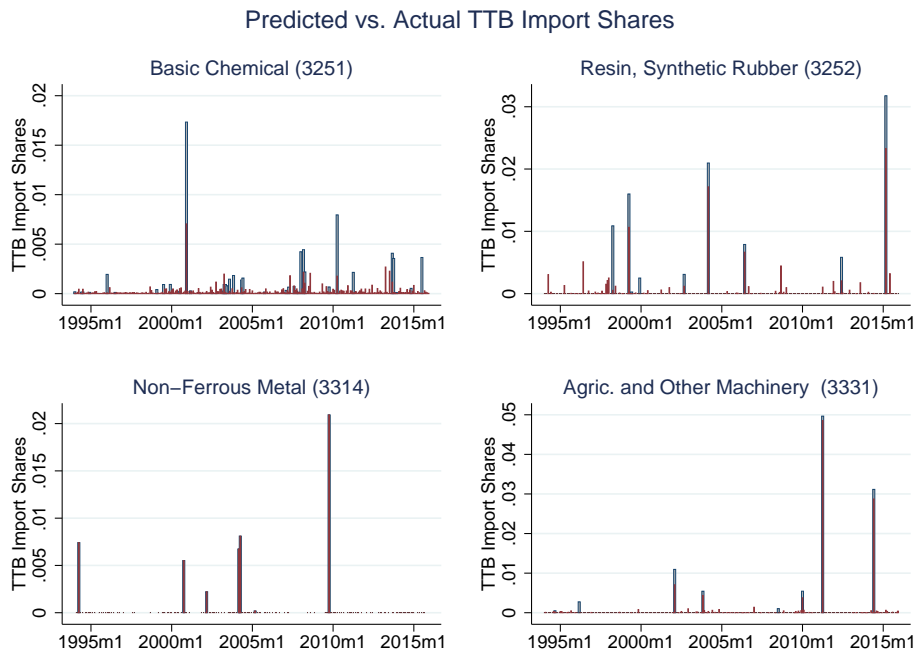


Figure A.4. Share of imports affected by antidumping investigations in selected NAICS-4 industries (blue histograms) and predicted values from the fractional-response model (red histograms).

Table A.1: Market-to-Book and Employment Growth, Granger Causality Test

Dep. Variable: $\Delta L_t$	Industry NAICS-4						
	3311	3251	3329	3312	3252	3314	3331
$M/B_{t-1}$	0.013*** (0.005)	0.008** (0.003)	0.004* (0.002)	0.002 (0.004)	-0.001 (0.003)	0.003 (0.004)	0.006** (0.002)
$M/B_{t-2}$	-0.005 (0.007)	-0.006 (0.004)	0.001 (0.003)	-0.005 (0.005)	0.000 (0.004)	-0.001 (0.005)	-0.001 (0.003)
$M/B_{t-3}$	-0.001 (0.005)	0.001 (0.003)	-0.003 (0.002)	0.004 (0.004)	0.004 (0.003)	-0.000 (0.004)	-0.001 (0.002)
$\Delta L_{t-1}$	1.187*** (0.064)	0.899*** (0.062)	1.198*** (0.064)	1.092*** (0.064)	1.147*** (0.063)	0.955*** (0.063)	1.197*** (0.063)
$\Delta L_{t-2}$	-0.089 (0.098)	0.185** (0.084)	0.106 (0.099)	0.147 (0.093)	-0.280*** (0.096)	0.151* (0.086)	0.030 (0.099)
$\Delta L_{t-3}$	-0.116 (0.098)	0.044 (0.084)	-0.195* (0.099)	-0.138 (0.093)	0.161 (0.098)	0.039 (0.087)	-0.193** (0.098)
$\Delta L_{t-4}$	0.070 (0.100)	-0.030 (0.084)	-0.148 (0.098)	-0.203** (0.094)	-0.112 (0.098)	-0.017 (0.087)	-0.077 (0.099)
$\Delta L_{t-5}$	-0.103 (0.102)	-0.040 (0.085)	0.049 (0.099)	0.078 (0.094)	0.131 (0.098)	-0.077 (0.087)	0.029 (0.100)
$\Delta L_{t-6}$	-0.109 (0.101)	-0.041 (0.085)	-0.059 (0.098)	-0.078 (0.094)	-0.034 (0.098)	-0.100 (0.086)	0.031 (0.099)
$\Delta L_{t-7}$	0.175* (0.102)	-0.123 (0.085)	0.067 (0.097)	0.208** (0.096)	-0.032 (0.098)	-0.069 (0.086)	-0.103 (0.098)
$\Delta L_{t-8}$	-0.021 (0.102)	-0.095 (0.085)	0.081 (0.097)	-0.114 (0.098)	0.070 (0.097)	0.063 (0.086)	0.135 (0.095)
$\Delta L_{t-9}$	-0.122 (0.104)	0.039 (0.085)	-0.279*** (0.098)	-0.076 (0.096)	-0.069 (0.097)	-0.096 (0.087)	-0.087 (0.093)
$\Delta L_{t-10}$	0.074 (0.105)	0.159* (0.085)	0.017 (0.101)	-0.177* (0.094)	-0.027 (0.097)	-0.004 (0.087)	-0.131 (0.093)
$\Delta L_{t-11}$	-0.103 (0.104)	0.143* (0.084)	0.148 (0.101)	0.241** (0.095)	-0.068 (0.096)	0.229*** (0.086)	0.150 (0.093)
$\Delta L_{t-12}$	0.067 (0.064)	-0.205*** (0.062)	-0.018 (0.064)	-0.054 (0.064)	0.022 (0.063)	-0.143** (0.063)	-0.047 (0.061)
R-squared	0.966	0.952	0.983	0.957	0.953	0.950	0.976
N	264	264	264	264	264	264	264
Joint F-test (p-value)	0.001	0.037	0.048	0.100	0.629	0.591	0.015

Table A.2 First-Stage Regression Coefficients.

Dep. Variable: TTB (Import Shares)	Industry NAICS-4								
	3311	3251	3329	3312	3326	3252	3314	3331	Panel
$\Delta L_{t-1}$	-0.024 (0.073)	-0.010 (0.011)	-0.164** (0.071)	0.058 (0.144)	-0.842* (0.496)	-0.482** (0.189)	0.268*** (0.020)	-0.033 (0.025)	-0.097** (0.046)
$\Delta L_{t-2}$	-0.073 (0.078)	-0.002 (0.009)	0.086 (0.118)	-0.052 (0.109)	0.147 (0.151)	-0.308* (0.178)	-0.242*** (0.024)	-0.030 (0.021)	-0.038 (0.046)
$\Delta L_{t-3}$	-0.108 (0.091)	0.026 (0.019)	-0.468*** (0.154)	0.132 (0.296)	-0.062 (0.124)	0.368*** (0.127)	0.291*** (0.020)	0.069** (0.032)	-0.020 (0.046)
$\Delta L_{t-4}$	-0.245** (0.106)	0.023* (0.012)	0.069 (0.053)	0.067 (0.111)	0.328 (0.281)	0.368*** (0.115)	-0.056*** (0.016)	0.064* (0.037)	-0.010 (0.046)
$\Delta L_{t-5}$	0.099 (0.091)	-0.017* (0.010)	0.256** (0.104)	-0.043 (0.124)	0.278 (0.270)	-0.362* (0.220)	0.301*** (0.019)	-0.037* (0.021)	-0.006 (0.047)
$\Delta L_{t-6}$	0.290** (0.118)	-0.011 (0.015)	-0.229*** (0.075)	-0.245 (0.297)	0.943 (0.577)	-0.083 (0.193)	-0.171*** (0.016)	-0.058** (0.027)	-0.047 (0.047)
$\Delta L_{t-7}$	0.001 (0.097)	0.032** (0.015)	-0.005 (0.063)	0.027 (0.035)	-1.747 (1.130)	-0.196 (0.152)	-0.150*** (0.024)	-0.057*** (0.020)	-0.016 (0.047)
$\Delta L_{t-8}$	-0.013 (0.123)	-0.008 (0.013)	0.176* (0.094)	-0.025 (0.035)	-1.041 (0.712)	-0.094 (0.195)	-0.081*** (0.020)	-0.070** (0.034)	-0.007 (0.047)
$\Delta L_{t-9}$	-0.103 (0.095)	0.013 (0.012)	-0.002 (0.055)	0.182 (0.245)	-0.404 (0.370)	0.153 (0.113)	-0.043*** (0.008)	0.024 (0.023)	0.081* (0.047)
$\Delta L_{t-10}$	-0.083 (0.096)	-0.007 (0.018)	-0.319*** (0.114)	-0.192 (0.197)	0.993 (0.617)	-0.114 (0.266)	-0.085*** (0.013)	0.022 (0.020)	-0.085* (0.047)
$\Delta L_{t-11}$	0.160 (0.124)	-0.007 (0.026)	0.108 (0.073)	0.045 (0.050)	1.236 (0.851)	0.448 (0.273)	-0.059*** (0.013)	-0.017 (0.035)	0.050 (0.047)
$\Delta L_{t-12}$	-0.140 (0.096)	-0.001 (0.009)	-0.016 (0.073)	0.228 (0.323)	0.016 (0.183)	-0.121 (0.109)	0.138*** (0.014)	-0.053*** (0.020)	-0.045 (0.047)
$M/B_{t-1}$	-0.005 (0.007)	-0.000 (0.000)	-0.002 (0.002)	0.004 (0.005)		-0.009** (0.004)	0.012*** (0.001)	-0.002*** (0.000)	-0.002 (0.002)
$M/B_{t-2}$	0.007 (0.008)	0.000 (0.001)	0.004 (0.003)	-0.005 (0.006)		0.017*** (0.005)	-0.011*** (0.001)	0.002** (0.001)	0.003 (0.002)
$M/B_{t-3}$	-0.009 (0.006)	-0.000 (0.001)	-0.001 (0.003)	0.001 (0.002)		-0.009* (0.005)	-0.004*** (0.001)	0.000 (0.001)	-0.002 (0.002)
Aggregate Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Time and Industry FE	No	No	No	No	No	No	No	No	Yes