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SELF-HARMING TRADE POLICY? PROTECTIONISM AND PRODUCTION NETWORKS

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Self-Harming Trade Policy? Protectionism and Production Networks
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ABSTRACT

Using monthly data on temporary trade barriers (TTBs), we estimate the dynamic employment effects of protectionism through vertical production linkages. First, exploiting procedural details of TTBs and high-frequency data, we identify movements in protectionism exogenous to economic fundamentals. We then use input-output tables to construct measures of protectionism affecting downstream producers. Finally, we estimate panel local projections using the identified trade-policy shocks. Protectionism has small and insignificant beneficial effects in protected industries. In contrast, the effects in downstream industries are negative, sizable, and significant. The employment decline follows an increase in intermediate-inputs and final goods prices.

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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 an isolated episode. Hidden behind unchanging tariff policies, governments have been using temporary trade barriers (TTBs)—antidumping, countervailing duties, and safeguards—to restrict trade in intermediate inputs since 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 discussions on the effects of protectionism contrast potential gains in protected industries and possible negative effects on downstream sectors—the producers that use protected goods as intermediate inputs.[1] However, despite the relevance of supply-chains considerations, econometric evidence on the effects of protectionism through vertical production linkages remains scant. We address this issue by studying the employment effects of TTBs in protected and downstream industries.

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 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 tariffs, 10 to 20 times higher than MFN tariffs on average (Blonigen and Prusa, 2015). Fourth, the

[1] 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.

availability of high-frequency data allows us to exploit institutional features of TTBs' procedures that impose short-run restrictions relevant for the identification of trade policy shocks. Fifth, the use of TTBs allows us to conduct the analysis at a disaggregated level—NAICS 4-digit industries—encompassing 70 narrowly defined manufacturing sectors. This level of aggregation allows us to measure accurately input-output linkages.

We construct monthly time series for the sectorial 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 an investigation discloses evidence on the margins of dumping and/or foreign governments' subsidies which ultimately determine the size of the 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 movements in protectionism that are plausibly unanticipated and not correlated with economic fundamentals. Our approach builds on a consolidated strategy in the monetary and fiscal policy literature, following the seminal work by Romer and Romer (2004). The idea is to purge the series of interest (TTBs protection) of movements taken in response to past, current, and expected dynamics in the outcome variable of interest (employment growth). The remaining variation allows us to identify the effects of protectionism on employment within and across industries, even in the scenario in which such variation is not strictly exogenous, i.e., when other factors not affecting employment dynamics drive the residual TTBs dynamics.

We consider two alternative and complementary approaches to identify trade-policy shocks. One focuses on within-industry time-series variation, while the other one uses the panel dimension of the data. In both cases, we exploit regulation-induced lags in the opening of an investigation to impose short-run restrictions—TTBs cannot react to economic shocks within a month. We then control for past economic conditions and measures that capture expected economic outcomes. In particular, using firm-level data, we construct for each industry a benchmark measure of expected returns used in the finance literature, the market-to-book ratio (e.g., Pontiff and Schall, 1998, and subsequent literature). With panel data, we also include industry and time fixed effects, stronger controls for unobserved heterogeneity and common shocks.

We then combine the trade-policy shocks with NAICS 4-digit total requirements input-output tables to construct a measure of 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).

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. Across specifications, 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 employment increase at most equal to 0.15 percentage points on average. The response turns negative after approximately one year. 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, heterogenous responses across producers (e.g., a different exposure to products covered by TTBs), as well as the presence of offsetting forces determining industry's output demand (e.g., expenditure switching versus negative income effects).

Second, protectionism has negative, persistent, and statistically-significant effects on employment in downstream industries. Our estimates imply that a uniform 2 percentage-point increase in the share of imports subject to TTBs in upstream industries generates an average employment decline up to 1 percentage point after two years.

Third, the downstream employment loss is accompanied by a statistically significant increase in both intermediate-input and final producer prices. From a timing perspective, the peak of the price increase precedes the peak of the employment decline, suggesting that it is indeed a loss of competitiveness that causes employment losses. In addition, employment falls more 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.[2] Erbahar and Zi (2017) show that protection granted to intermediate manufacturers leads to petition for protection by their downstream users. Finally, Baqaee 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 dynamic effects of protectionism through vertical linkages, complementing the perspective of these studies. In complementary and subsequent work, Bown, Conconi, Erbahar, and Trimarchi (2020) use data on TTBs to study the long-run effects of trade protection along supply chains.

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 sectorial 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.[3] 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 the identification of the effects of a given policy change more challenging.

A recent literature studies the effects of protectionism abstracting from the role of production

[2]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.

[3]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)

networks. A strand of the literature focuses on the trade effects of antidumping. Durling and Prusa (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 outcomes. 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.[4] Finally, few contributions study the effects of TTBs on the performance and behavior of protected firms.[5] 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.

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.[6] In subsequent work, Flaaen and Pierce (2019) find that tariff increases enacted in 2018 are associated with relative reductions in U.S. manufacturing employment and relative increases in producer prices. Rising input costs and retaliatory tariffs contribute to the negative relationship. We complement the perspective of these studies by providing systematic evidence on the dynamic effects of protectionism on economic activity in protected industries and through production networks using

[4] 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 variations in trade policy that is exogenous with respect to economic fundamentals.

[5] 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).

[6] 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.

a novel time-series identification of trade policy shocks.

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).

Outline The paper proceeds as follows. Section 2 reviews key features of TTBs data. 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 most important policy tool to impose tariffs above MFN levels within the rules of WTO. 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. Antidumping initiatives account for the vast majority of TTBs—across countries, they represent between 80 and 90 percent of all initiatives.

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. Overall, it takes longer than a month to open a new investigation. We will exploit such decision lags to identify trade-policy changes that are exogenous relative to economic fundamentals. 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 anticipatory effects, we focus on investigations rather than on their final outcome.[7] 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.[8] 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 $T = 264$ 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 for some industries. In Section 6, we show that considering

[7] 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.

[8] 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 part of the investigation.

global safeguards does not qualitatively affect the results.

The use of TTBs is concentrated in a few industries—e.g., base metals and metal products, chemicals and allied products, 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 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 frequent user is the "Iron, Steel and Ferro-Alloy" industry, 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 the widespread majority of investigations end up with the imposition of duties. For instance, in "Iron, Steel and Ferro-Alloy," tariffs are the final outcome in 82% of the investigations. In other industries, all episodes led to the imposition of tariffs. The applied tariff rates are also very large, 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 sectorial import share affected by TTBs episodes. Column 5 reports the maximum value of this import share. The largest import coverage occurs in "Steel Product Manufacturing from Purchased Steel" (11.09%), with a peak equal to 31.5%. For the most important user of TTBs (“Iron, Steel and Ferro-Alloy”), TTBs episodes involve approximately 2% of industry imports on average, although the largest episode covers 9% of imports. Finally, column 6 shows that the top TTBs users display high imports-to-output ratios.

2.1.2 TTBs Users and Production Linkages

We now turn to the relevance of TTBs for downstream industries. We measure the importance of the industries reported in Table 1 as intermediate-input suppliers in the manufacturing sector. We use direct-requirements input-output tables from the U.S. Bureau of Economic Analysis. 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.[9] 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 input indirectly).

Figure 1 plots the U.S. production network for the year 2007 using the direct-requirements table. It shows the linkages between each manufacturing industry and the sectors that use the 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. Thus, the figure shows the centrality of industries that actively use TTBs in the production network.

Table 2 provides additional quantitative information. The first column measures the output share of each industry relative to the total U.S. manufacturing output in 2007. Column 2 and 3 report, respectively, the average direct requirement and the maximum requirement in downstream industries. Column 4 and 5 report analogous figures using total requirements. As shown by the table, the largest TTBs users are also 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).

[9] 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.

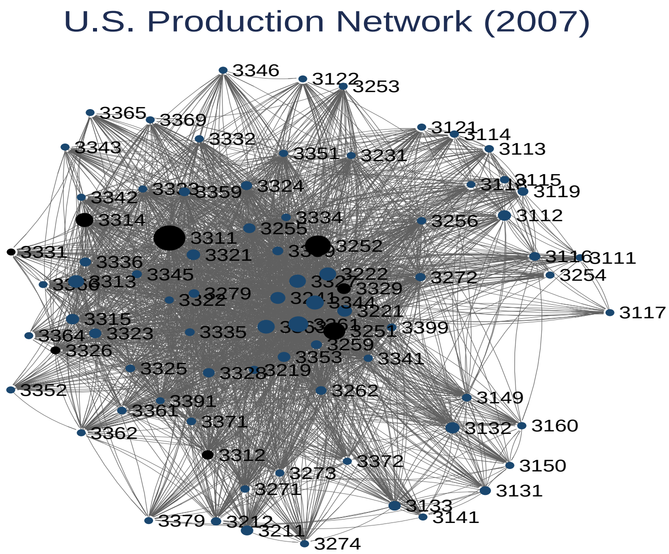

Figure 1. Production network implied by 2007 NAICS 4-digit input-output tables.

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 sectorial shares of imports subject to new investigations in each month. We use previous-year import data to construct the weights. We focus on the import coverage of TTBs to combine information on both extensive- and intensive-margin variation in import protection. Thus, 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 sectorial share of imports subject to new investigations in a given month:

$$\tau_{it} \equiv \sum_{k} \sum_{j} \omega_{ij}^{k} \mathcal{I}_{ijt}^{k}, \tag{1}$$

where ω_{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

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%
Total	**10.40%**	**9.94%**		**24.90%**	

investigations on 27 imported products against 11 trading partners.[10] 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. Notice that while the use of previous-year weights in the construction of τ_{it} addresses endogeneity concerns in the econometric analysis, it potentially introduces measurement error. In Section 6, we show the results are robust to considering two alternative trade-policy measures. One only uses the extensive margin of TTBs, while the second one constructs the weights using the full-sample average import shares.

Figure 2 plots time series data for τ_{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).[11] Over time, the industry "Iron, Steel and Ferro-Alloy" features the largest variation in the share of imports subject to investigations. Across sectors, τ_{it} displays weak autocorrelation, averaging to 0.004. Similarly, τ_{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.

Figure 3 plots τ_{it} (again measured on the left axis) and the growth rate of industry producer prices (measured on the right axis). The figure shows that some of the spikes in TTBs are preceded by a price decline, which again suggests that part of the variation in protectionism may reflect

[10] The trading partners were Argentina, China, India, Indonesia, Kazakhstan, Netherlands, Romania, South Africa, Taiwan, Thailand and Ukraine.

[11] See Appendix B for the remaining industries reported in Table 1.

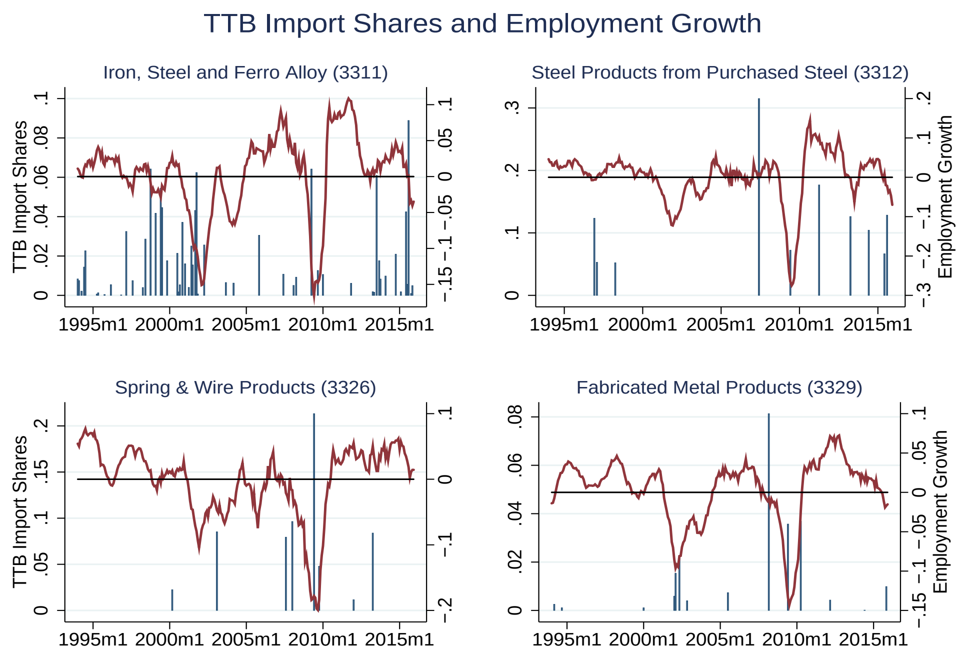

Figure 2. Share of imports affected by TTBs investigations in selected NAICS-4 industries (histograms) and employment growth (continuous line).

industry economic developments.

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 exogenous with respect to industry-employment variation. In the second stage, we use the identified TTBs shocks to estimate the monthly response of industry employment following protectionism. While endogeneity is less of a concern when studying the downstream effects of upstream protection—it is unlikely that downstream economic forces are the primary driver of TTBs in upstream industries—we control for downstream conditions and aggregate shocks in the first stage of the analysis.

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.

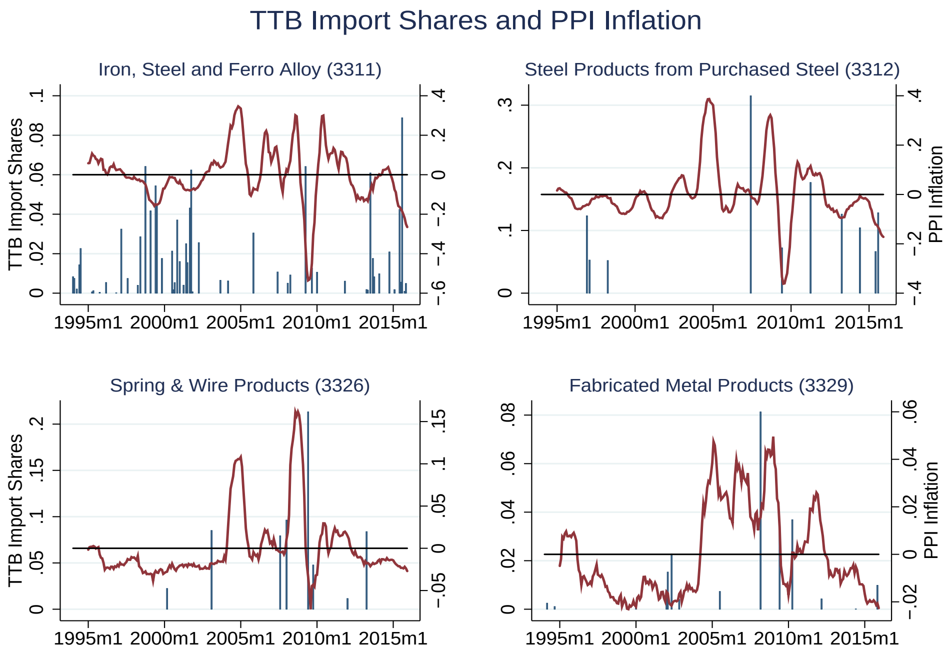

Figure 3. Share of imports affected by TTBs investigations in selected NAICS-4 industries (histograms) and producer price inflation (continuous line).

3.1 Identification Strategy

We build on a consolidated identification strategy in the monetary and fiscal policy literature. Following the seminal work by Romer and Romer (2004), the idea is to purge a given series (TTBs protection, τ_{it}, in our case) of movements taken in response to past, current, and expected dynamics of the outcome variable of interest (e.g., employment). Once this is accomplished, we use the remaining variation to identify the effect of protectionism in the second stage of the empirical analysis.

The identification proceeds as follows. We exploit regulation-induced lags in the opening of an investigation to impose short-run restrictions that address simultaneity concerns—as discussed in Section 2, TTBs investigations cannot react to economic shocks within a month. We then use two alternative (and complementary) methods to control for past economic conditions and measures that capture expected economic outcomes. The first approach exploits within-industry time series variation in TTBs. The second approach uses the panel dimensions of the data, including time and industry fixed effects. In both cases, we regress τ_{it} on a set of economic controls. Building on the insights from the theoretical literature on the economic determinants of TTBs, we include lags of the monthly growth rate of employment, employment in downstream industries, prices, and additional time-varying industry-specific controls. The approach ensures that the identified trade-policy shocks are orthogonal to past dynamics in the outcome variables of interest.

While the nature of TTBs is intrinsically backward looking, we also consider the possibility that demand for protection is forward-looking. We use firm-level data to construct a benchmark measure of monthly industry-level expected returns (the market-to-book ratio) and also consider macroeconomic forecast data.

As highlighted by the trade and antitrust literature, the remaining (identified) variation in TTBs reflects several factors unrelated to cyclical economic conditions. Such factors include political pressure (lobbying) to affect the domestic market structure and exports abroad ("tit-for-tat" strategies), prevention of foreign predatory pricing, retaliation against foreign protectionism, and strategies to coordinate and support collusive behavior (Blonigen and Prusa, 2015).[12]

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 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 $[0, 1]$.[13] In addition, fractional response models capture 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. Notice that while the share of goods subject to TTBs, τ_{it}, is equal to zero in several months, the zero values do not reflect selection bias (i.e., truncation or censoring).

We choose the set of control variables according to various criteria. First, the estimated residuals must be orthogonal with respect to previous variation in the outcome variables of interest. For this reasons, we include lags of employment growth (both in the protected industry and in downstream

[12] The main users of TTBs are sectors with a relatively low numbers of firms and significant economies of scale (e.g., steel, chemicals). In these "oligopolistic" sectors, firms face relatively lower collective action problems, facilitating the lobbying process.

[13] 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.

industries). Second, following the technical criteria specified in the WTO Antidumping Agreement (and the suggestive evidence in Figure 3), we control for industry prices—intuitively, industries that face rapidly falling prices are more likely to pursue an investigation. Third, following the existing theoretical literature about the economic determinants of TTBs, we include the exchange rate and industry imports. Fourth, we consider the possibility that TTBs also depend on expected future economic outcomes, constructing measures of industry-level expected returns and including the forecast of aggregate industrial production.

We estimate the following model

$$\tau_{it} = G\left(\mu_{it}\right) + \varepsilon_{it}, \tag{2}$$

where the conditional mean of τ_{it} is defined by

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

The term μ_{it} contains both industry-specific and aggregate variables:

$$\mu_{it} \equiv \delta_i + \sum_{\kappa=1}^{p_L} \phi_{L_i}^{\kappa} \Delta L_{it-\kappa} + \sum_{\kappa=1}^{p_{LIO}} \phi_{L_i^{IO}}^{\kappa} \Delta L_{it-\kappa}^{IO} + \sum_{\kappa=1}^{p_P} \phi_{P_i}^{\kappa} \Delta P_{it-\kappa} + \sum_{\kappa=1}^{p_{MB}} \phi_{MB_i}^{\kappa} MB_{it-\kappa} + \sum_{\kappa=1}^{p_x} \mathbf{\Phi}_x^{\kappa} \mathbf{x}_{t-\kappa}, \tag{3}$$

where δ_i is a constant term and $\mathbf{x}_t$ is a vector of aggregate controls. Industry-level variables include lags of the growth rate of employment (ΔL_{it}), the growth rate of employment in downstream industries (ΔL_{it}^{IO}), producer-price inflation (ΔP_{it}), and 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. In Section 6, we present results also including hourly earnings (Δw_{it}) and imports (ΔI_{it}).[14] Aggregate controls include the growth rate of the real exchange rate and 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

[14] We do not include Δw_{it} and ΔI_{it} in the baseline specification for two reasons. First, for some industries, data on hourly earnings are only available at the NAICS 3-digit level of aggregation. Second, since we construct τ_{it} using previous-year imports data, the inclusion of ΔI_{it} could potentially introduces endogeneity—we deal with this issue in Section 6.

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 (ΔL_{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 influence current demand for trade protection.

We construct employment growth in downstream industries, ΔL_{it}^{IO}, as follows:

$$\Delta L_{it}^{IO} \equiv \sum_{j \neq i} \lambda_{ij} \Delta L_{jt},$$

where the fixed weight λ_{ij} reflects the use of sector j of the output of industry i. The definition of ΔL_{it}^{IO} implies that a change in employment growth in industry j is more important for industry i when the output share of sector i in sector j is higher. We compute each weight λ_{ij} using the 2007 total-requirements input-output table.[15]

For parsimony, we do not include lags of the dependent variable given the absence of autocorrelation in the raw series for τ_{it}—the autocorrelation function is never significantly different from zero across industries. We include twelve lags for the growth rate of employment, as well as three lags for ΔL_{it}^{IO}, ΔP_{it}, $MB_{it-\kappa}$, and the aggregate variables.

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. However, fixed effects potentially remove variation in τ_{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 identification strategy.

We consider the following regression:

[15] The use of fixed weights has the advantage of addressing endogeneity concerns in the construction of ΔL_{it}^{IO} (at the cost of potentially introducing measurement error).

$$\tau_{it} = \alpha_i + \sum_{\kappa=1}^{p_L} \phi^{\kappa}_{L_i} \Delta L_{it-\kappa} + \sum_{\kappa=1}^{p_{L^{IO}}} \phi^{\kappa}_{L^{IO}_i} \Delta L^{IO}_{it-\kappa} + \sum_{\kappa=1}^{p_P} \phi^{\kappa}_{P_i} \Delta P_{it-\kappa} + \sum_{\kappa=1}^{p_{MB}} \phi^{\kappa}_{MB_i} MB_{it-\kappa} + \eta_t + \varepsilon_{it}, \quad (4)$$

where α_i is an industry fixed effect, η_t is a time t fixed effect, and ε_{it} is the industry-specific prediction-error term. 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 common shocks across industries. We use the same symbol (ε_{it}) to denote the residuals from the panel and time-series regressions to simplify the notation in the second stage. It remains understood that the estimated residuals differ across the two models.

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 α_i is correlated with industry controls. For instance, with a small T, both OLS and the within-group estimator yield inconsistent estimates.[16] 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.

3.2 Results

The estimated residuals from equation (2) and (4) are the identified TTBs shocks. Regardless of the econometric model (time-series or panel), the shocks have plausible statistical properties: they are serially uncorrelated and not correlated across industries. To provide a formal assessment, we run a Ljung-Box test to detect the presence of serial autocorrelation on each industry-specific residual $\hat{\varepsilon}_{it}$. We also consider a multivariate Ljung-Box test to detect potential correlation across industries. As shown in Table 3, we cannot reject the null hypotheses of zero serial autocorrelation and zero contemporaneous cross-correlation at the 5% significance level.

Figure 4 plots the predicted sectorial TTBs import shares estimated by 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 predicted values account well for several spikes in TTBs across industries, in particular in the second part of the 2000s. When considering spikes in τ_{it} that are larger than

[16] OLS suffer from an omitted variable bias, since α_i is part of the error term ε_{it}. The within-group estimator induces correlation between the regressors and the error term when demeaning the data (Nickell, 1981)

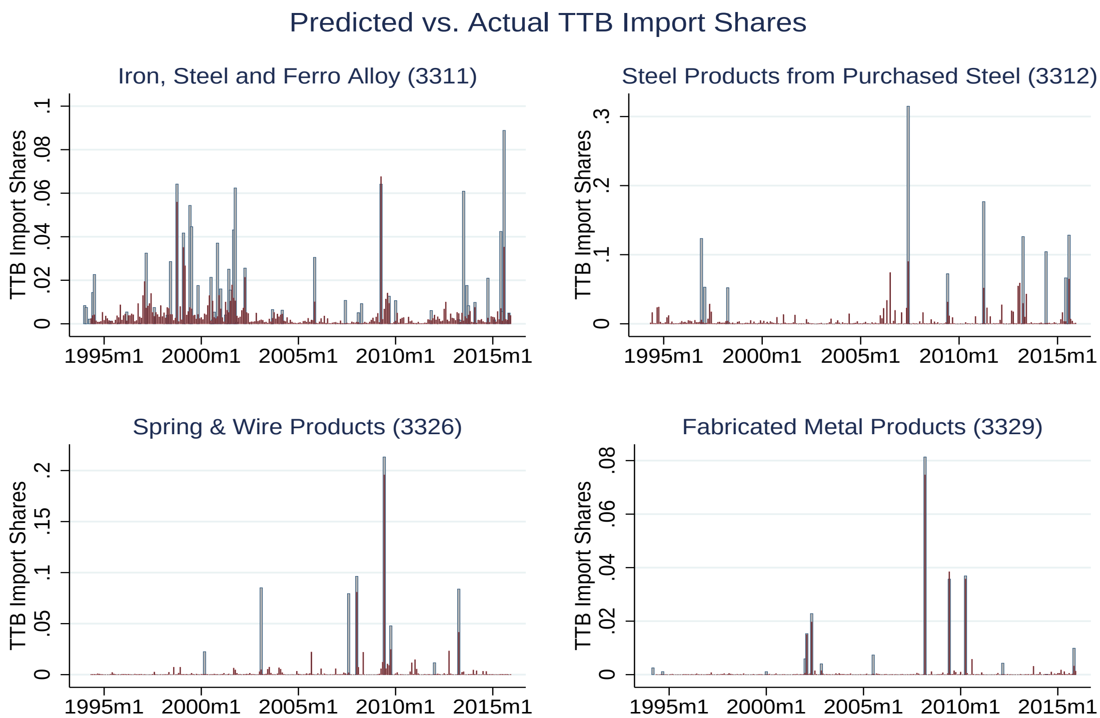

Figure 4. Share of imports affected by antidumping investigations in selected NAICS-4 industries (blue histograms) and predicted values from the fractional-response model (red histograms).

one standard deviation, the predicted τ_{it} explains, on average, 44% of the actual variation. At the same time, there remains unexplained variation in TTBs in various episodes. The pseudo-R^2 varies between 43% and 9% across industries (see Table 3).

Table 3: First-Stage Estimation

		NAICS-4 Industry Code							
Identification Approach	Statistics	3311	3251	3329	3312	3326	3252	3314	3331
Time Series	Pseudo R-squared	0.11	0.09	0.39	0.22	0.35	0.34	0.43	0.34
(Fractional Logit)	Industry Ljung-Box Test (p-value)	0.15	0.56	0.99	0.94	0.98	0.89	1.00	0.92
	Joint Ljung-Box Test (p-value)				0.15				
Panel	R-squared				0.18				
	Industry Ljung-Box Test (p-value)	0.20	0.67	0.35	0.31		0.27	0.38	0.85
	Joint Ljung-Box Test (p-value)				1.00				

The trade-policy shocks identified with the panel approach—equation (4) above—are positively correlated with the estimated residuals from the fractional-response model. For the sector "Iron, Steel and Ferro Alloy"—the largest users of TTBs in our sample—the correlation is 0.76, while on average it is 0.41.[17]

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 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:

$$\hat{\varepsilon}_{it}^{IO} \equiv \sum_{j \neq i} \theta_{ij} \hat{\varepsilon}_{jt}, \tag{5}$$

where the fixed weight θ_{ij} reflects the contribution of sector j to the output of industry i.[18] 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 θ_{ij} using the 2007 total-requirements input-output table.

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

[17] 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 and prices 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.

[18] 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, the results are robust to expressing each $\hat{\varepsilon}_{j,t}$ as a share of aggregate imports.

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.

We proceed as follows. First, we estimate the response of employment in protected industries. Second, we estimate the effects of protectionism through input-output linkages, i.e., the response of downstream-industry employment following the imposition of TTBs in upstream industries.

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 $t+h$. Let $\hat{\varepsilon}_{i,t}$ denote 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 $h = 0, .., H$:

$$\Delta L_{it+h} = \nu_{ih} + \gamma_h \hat{\varepsilon}_{it} + \psi_{th} + \epsilon_{it+h}, \tag{6}$$

where ν_{ih} denotes an industry fixed effect in the cumulative employment growth between time $t-1$ and $t+h$, ψ_{th} is a time fixed effects, and ϵ_{it+h} is the prediction error term. The industry fixed effect captures industry-specific trends in employment between $t-1$ 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 coefficient γ_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 γ_h for $h = 0, .., H$.

Two final observations are in order. First, following standard practice in the literature, we consider the cumulative employment difference, ΔL_{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 compute bootstrapped, clustered confidence intervals for each impulse response estimate (γ_h), accounting for the fact that $\hat{\varepsilon}_{it}$ is a generated regressor.[19]

[19] We conduct wild-bootstrap tests of the linear hypothesis $\gamma_h = 0$ for each $h = 0, .., H$. We consider 1000 replications and cluster both standard errors and boostrap 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:

$$\Delta L_{it+h} = \nu_{ih} + \gamma_h^{IO} \hat{\varepsilon}_{it}^{IO} + \psi_{th} + \epsilon_{it+h}. \tag{7}$$

As in equation (6), we include both industry and time fixed effects. The dynamic multipliers of interest are γ_h^{IO} for $h = 0, .., H$. 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). In section 6, we show the results are robust to the inclusion of additional time-varying industry-level controls (lags of the growth rate of employment and prices).

4.3 Results

Figure 5 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 γ_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 one year, 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, there could be heterogenous responses across producers within the protected industry, including a different exposure to products covered by TTBs. Third, as discussed in Barattieri, Cacciatore, and Ghironi (2018), trade protection triggers both expenditure switching and income effects, which are offsetting forces. Expenditure switching increases output demand in protected industries. The negative income effect due to overall higher prices has an opposite effect (as long as foreign and domestic products are

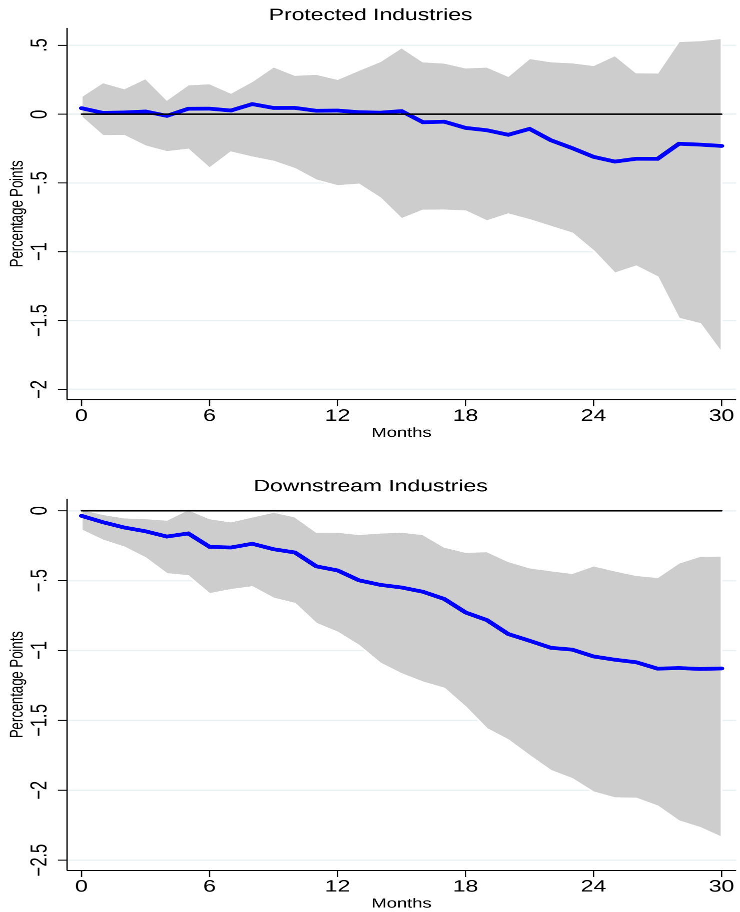

Figure 5. Impulse responses following a protectionism shock. *Top panel*: Average employment response in protected industries. *Bottom panel*: Average downstream-industry employment response. First-stage: Fractional-response model.

not perfect substitutes).

The picture is different when looking at the downstream effects of protectionism. The bottom panel in Figure 5 plots the employment response following protectionism in upstream industries. We consider a uniform 2 percentage-point increase in the share of imports subject to investigation in upstream industries.[20] On average, protectionism triggers statistically significant negative effects on downstream-industry employment. In particular, employment declines approximately by 1 percentage point after two years. 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).

[20]We set $\hat{\varepsilon}_{it}^{IO} \equiv 0.02 \sum_j \bar{\theta}_j$, where $\bar{\theta}_j \equiv [1/(N-1)] \sum_{j \neq i} \theta_{ij}$ weights the upstream (sector j) shock using the average input-output coefficient.

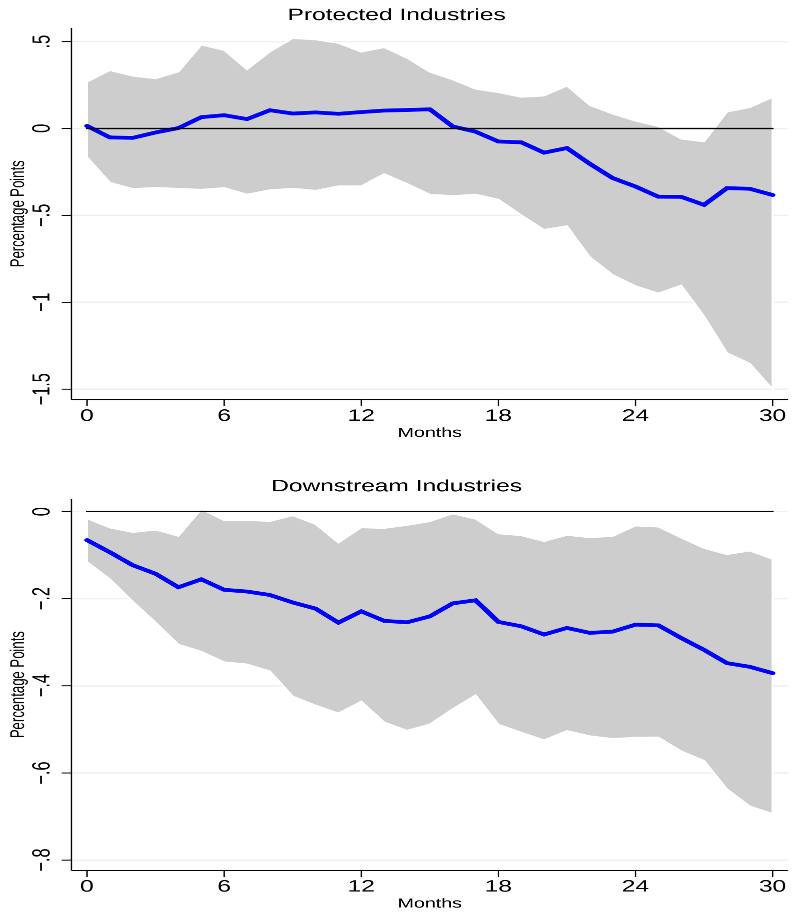

Figure 6. Impulse responses following a protectionism shock. *Top panel*: Average employment response in protected industries. *Bottom panel*: Average downstream-industry employment response. First-stage: Panel regression.

Figure 6 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 employment increase in protected industries, and it leads to an employment decline 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 difference in magnitude between the two econometric specifications (time series versus panel) reflects the inclusion of time and industry fixed effects in the panel regression—quantitatively the results become more similar when fixed effects are excluded from the regression.

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 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 downstream employment. 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 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 reduce competitiveness, lowering demand and employment.

In light of these considerations, we investigate the response of intermediate-input and final-producer prices in downstream industries. For each industry i, we construct an intermediate-input price index P^I_{it} as a weighted average of producer prices in upstream industries (i.e., industries whose output is used as an input in industry i):

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

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 (total requirements) 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 $\Delta P^I_{it+h} \equiv \log P^I_{it+h} - \log P^I_{it-1}$ 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:

$$\Delta P_{it+h} = \delta^h + \pi_h \hat{\varepsilon}^{IO}_{it} + \psi_{t+h} + \nu^{N4}_{ih} + \epsilon_{it+h}, \tag{8}$$

where $\hat{\varepsilon}^{IO}_{it}$ is estimated using the fractional-response model in (2) and $h = 0, .., H$. The coefficient

π_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 π_h for $h = 0, .., H$. Similarly, we estimate the response of intermediate-input producer prices:

$$\Delta P^I_{it+h} = \delta^h + \pi^I_h \hat{\varepsilon}^{IO}_{it} + \psi_{t+h} + \nu^{N4}_{ih} + \epsilon_{it+h}. \tag{9}$$

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

Panel A in Figure 7 shows the response of final-producer prices, while Panel B reports the response of intermediate-input prices. As before, we consider a uniform 2 percentage-point increase in the share of imports subject to TTBs. In both cases, prices increase, 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 perspective, the peak of the price increase precedes the peak of the employment decline, suggesting that a loss of competitiveness in downstream industries causes the employment decline.

5.2 Employment and Demand Elasticity

We finally explore whether the price elasticity of demand matters for the effects of protectionism on downstream-industry employment. 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.[21] 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 $h = 0, .., H$:

[21] The data are available at http://www.columbia.edu/~dew35/TradeElasticities/TradeElasticities.html.

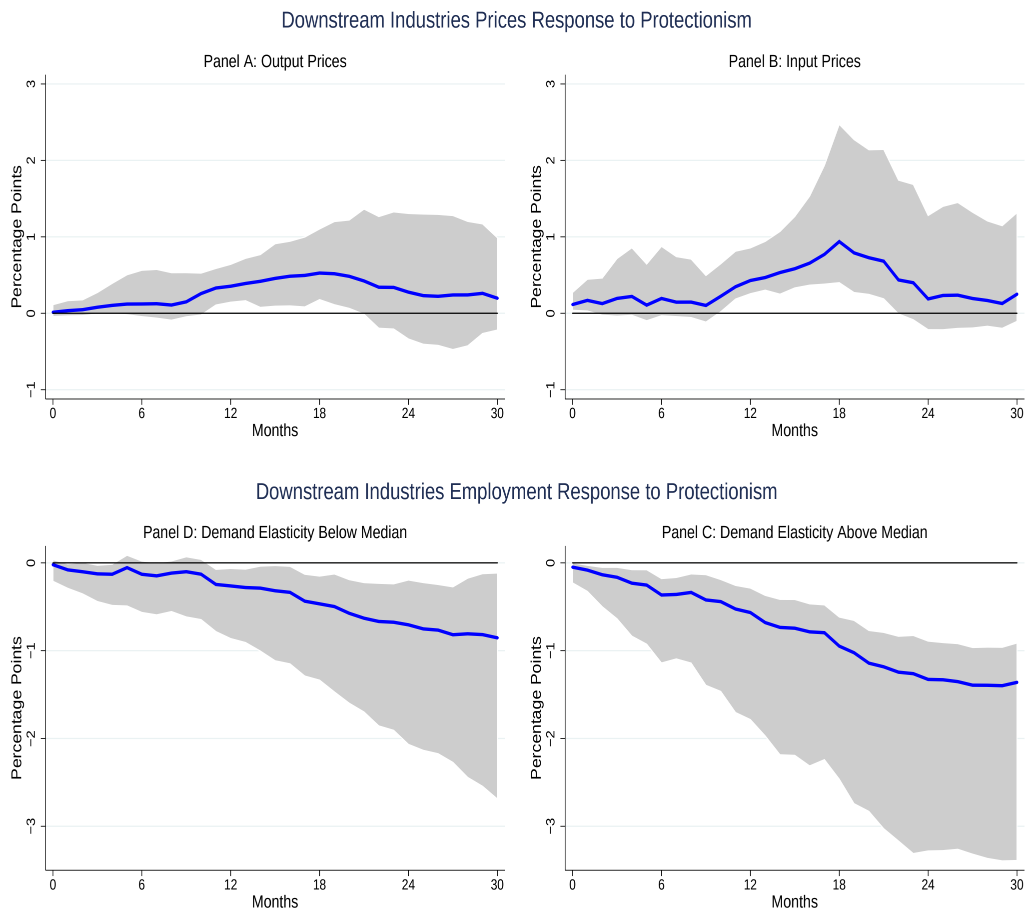

Figure 7. Impulse responses following protectionism in sourcing industries. *Panel A*: Producer-price response in downstream industries. *Panel B*: Intermediate-input price response in downstream industries. *Panel C*: Downstream-employment response in industries where the elasticity of substitution 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.

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

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 7 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

To conclude, 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 construct upstream exposure to TTBs, $\hat{\varepsilon}_{it}^{IO}$, alternative measures of protectionism, and a broader set of industry controls for both the first and second stage of the analysis.

6.1 Trade-Policy Shocks Identification

6.1.1 Probit Model

A concern in the first-stage estimation is measurement error due to the use of lagged imports when constructing the share of imports subject to protection (τ_{it}). To address this issue, we consider an alternative econometric model that only uses the extensive-margin variation in TTBs. For each industry i, 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 (zero otherwise):

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

Modeling the probability of an investigation (as opposed to the count of investigations) avoids

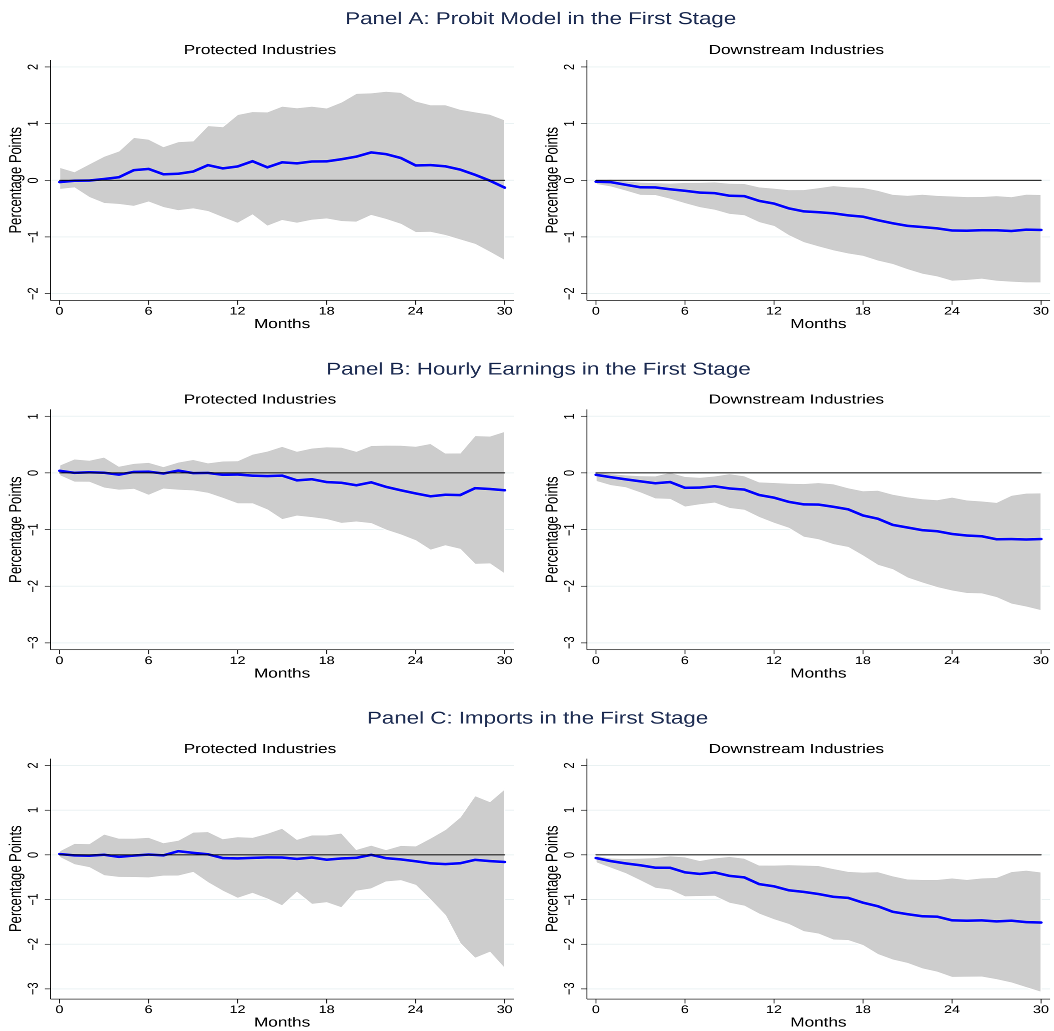

Figure 8. Impulse responses following a protectionism shock. *Panel A*: Probit model in the first-stage estimation. *Panel B*: Hourly earnings included in the first stage. *Panel C*: Imports included in the first stage. Sectorial imports share in τ_{it} are constructed using full-sample averages.

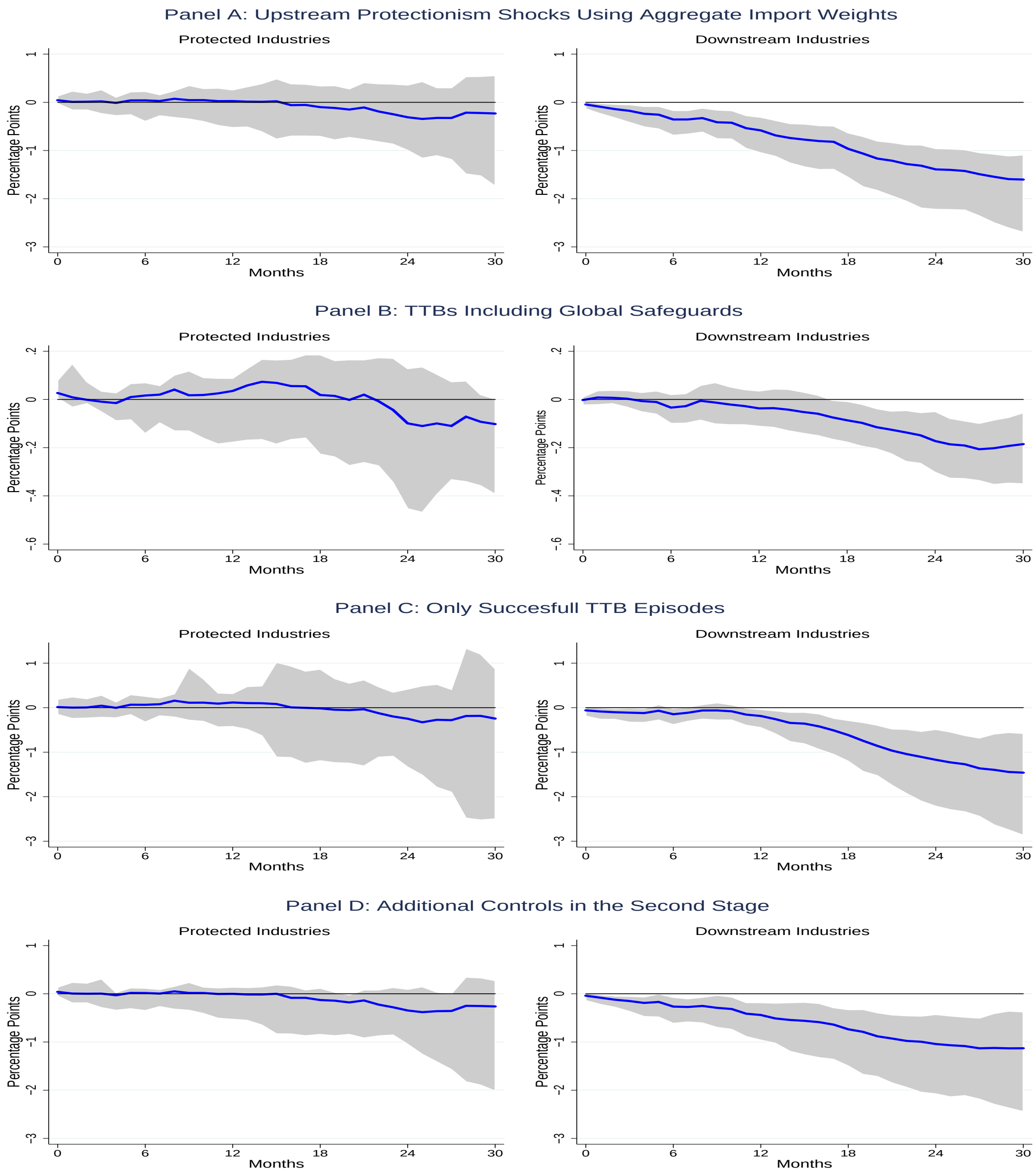

Figure 9. Impulse responses following a protectionism shock. *Panel A:* Average import shares when constructing τ_{it}. *Panel B*: TTBs include global safeguards. *Panel C*: Only episodes that end up with tariffs. *Panel D*: Additional controls in local projections: lags of the growth rate of employment and prices.

econometric complications.[22] Panel A in Figure 8 plots the local projection estimates using the probit model in the first stage of the estimation. We consider a unitary increase in both $\hat{\varepsilon}_{it}$ and $\hat{\varepsilon}_{it}^{IO}$. Relative to the benchmark model, the point estimates of the employment response in protected industries are more persistently positive, although they remain statistically insignificant. The employment decline in downstream industries remain statistically significant at all horizons.

6.1.2 Additional Controls: Hourly Earnings and Imports

As discussed in Section (3), we consider two additional industry-level controls in the first-stage regression: the growth rate of hourly earnings (Δw_{it}) and imports (ΔI_{it}).[23] When including ΔI_{it}, we construct the trade-policy measure τ_{it} using average import shares over the entire sample (rather than using previous-year import shares, as in the baseline specification). 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 bilateral, sectorial import share over the entire sample for each product under investigation. As shown by in Figure 9, the results are not substantially affected by the inclusion of hourly earnings (Panel B) or imports (Panel C).

6.2 An 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 sectorial import shares. An alternative approach 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. Also in this case we consider a uniform 2-percentage-point increase in upstream protectionism: $\hat{\varepsilon}_{it}^{IO} \equiv 0.02 \sum_j \bar{\theta}_j$, where $\bar{\theta}_j = [1/(N-1)] \sum_{j \neq i} \theta_{ij} s_j$. Panel A in Figure 9 shows that the results remain similar to

[22]The original count measure would require a discrete-choice model, which constraints more severely the estimation with time series data.

[23]For four industries—corresponding to the NAICS codes 3311, 3312, 3314, and 3326—hourly earnings are not available. For these three industries, we use NAICS 3-digit data.

the benchmark specification.

6.3 Alternative Measures of Protectionism

6.3.1 Global Safeguards

In the baseline specification, we exclude global safeguards from TTBs. Panel B in Figure 9 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."

6.3.2 Only Successful Investigations

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 do not lead to trade protection. Panel C in Figure 9 shows that the results are robust to this alternative choice.

6.4 Additional Controls in the Local Projections

Finally, we also verify the robustness of the results to the inclusion of six lags of industry employment and prices in the panel local projection. These additional variables control for the possibility that the synthetic measure ΔL_{it}^{IO} included in the first stage does not completely remove the effects of past downstream-employment dynamics on upstream protectionism. Panel D in Figure 9 shows the results remain substantially unaffected.

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 venues 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

Monthly data for industry employment and average hourly earnings for production and nonsupervisory employees are from the Current Employment Statistics of the Bureau of Economic Analysis.[24] Monthly producer-price data correspond to the Producer Price Index PC from the U.S. Bureau of Labor Statistics.[25] Monthly imports data are from the Census Bureau.[26] Aggregate data for the effective real exchange rate (all seasonally-adjusted) are from the Federal Reserve Economic Data. We use series RBUSBIS. Data on the median forecast of industrial production come from the Survey of Professional Forecasters. We use the series *dindprod6*.[27] The trade data used to construct the weights in (1) are bilateral HS 6-digit annual level of imports from Comtrade (downloaded through Wits).

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).[28] We convert SIC 4-digit firms' codes to NAICS 6-digit codes using the yearly conversion tables from Pierce and Schott (2009).[29] We then aggregate to NAICS 4-digit and

[24]The data are available at `https://download.bls.gov/pub/time.series/ce/`.

[25]NAICS 4-digit data are available from 2003:12 at: `https://download.bls.gov/pub/time.series/pc/pc.txt`. We extend the series to 1994:1 by using the discontinued series Producer Price Index PD, available at `https://download.bls.gov/pub/time.series/pd/`. Since the series is only available at SIC 4-digit level, we convert to NAICS 4-digit using Census concordances. Whenever more SIC codes correspond to a single NAICS 4-digit code, we use the median price across SIC industries. We link the series pre and post 2003 by using December 2003 as the base month.

[26]SITC 3-digit data are available from 1996:1 at:
`https://www.census.gov/foreign-trade/statistics/country/sitc/index.html`. We convert the series to NAICS 4-digit using Census concordances. In some instances, the same SITC code corresponds to multiple NAICS 4-digit codes. In this case, we allocate imports across the different NAICS code by using their average import share (relative to the SITC code total imports) in a given period.

[27]The series is available at `https://www.philadelphiafed.org/research-and-data/real-time-center`.

[28]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*).

[29]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).

construct the median market-to-book ratio for each industry.

B Other Descriptive Statistics

B.1 Share of Imports Subject to TTBs

Figure A.2 plots time series data for τ_{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. Figure A.3 plots τ_{it} (again measured on the left axis) and producer price inflation (measured on the right axis) for the same industries.

B.2 Market-to-Book Ratio

Figure A.4 and A.5 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 ΔL_{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 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 sectorial imports subject to TTBs following a unitary increase in the regressors.

Figure A.1 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.

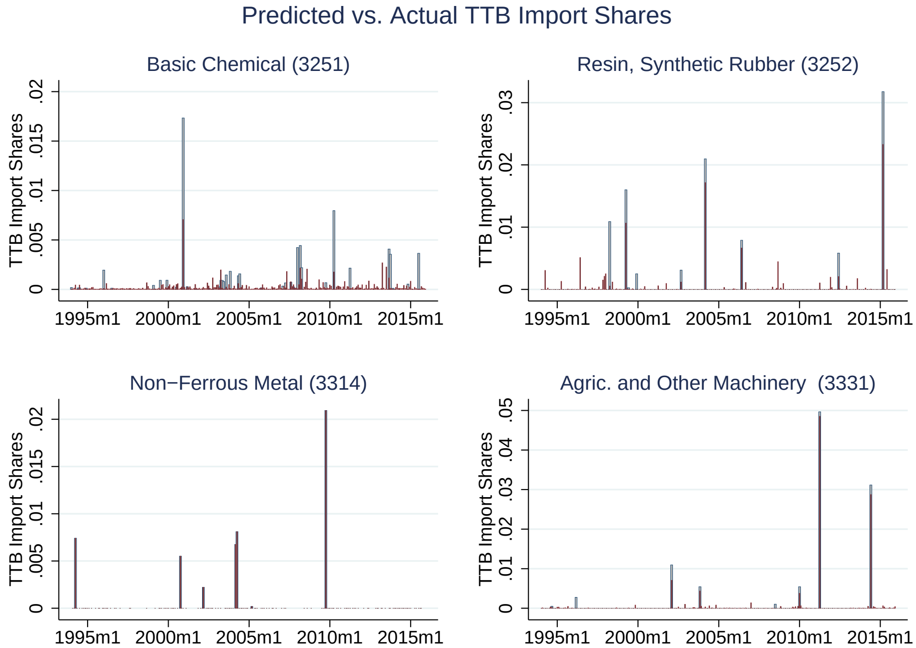

Figure A.1. Share of imports affected by antidumping investigations in selected NAICS-4 industries (blue histograms) and predicted values from the fractional-response model (red histograms).

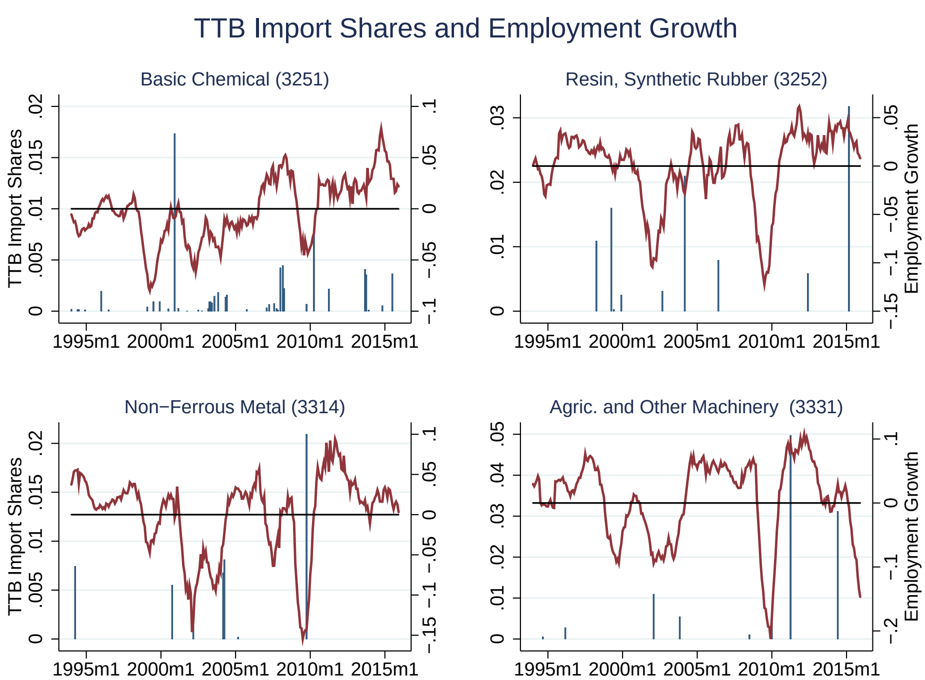

Figure A.2. Share of imports affected by TTBs investigations in selected NAICS-4 industries (histograms) and employment growth (continuous line).

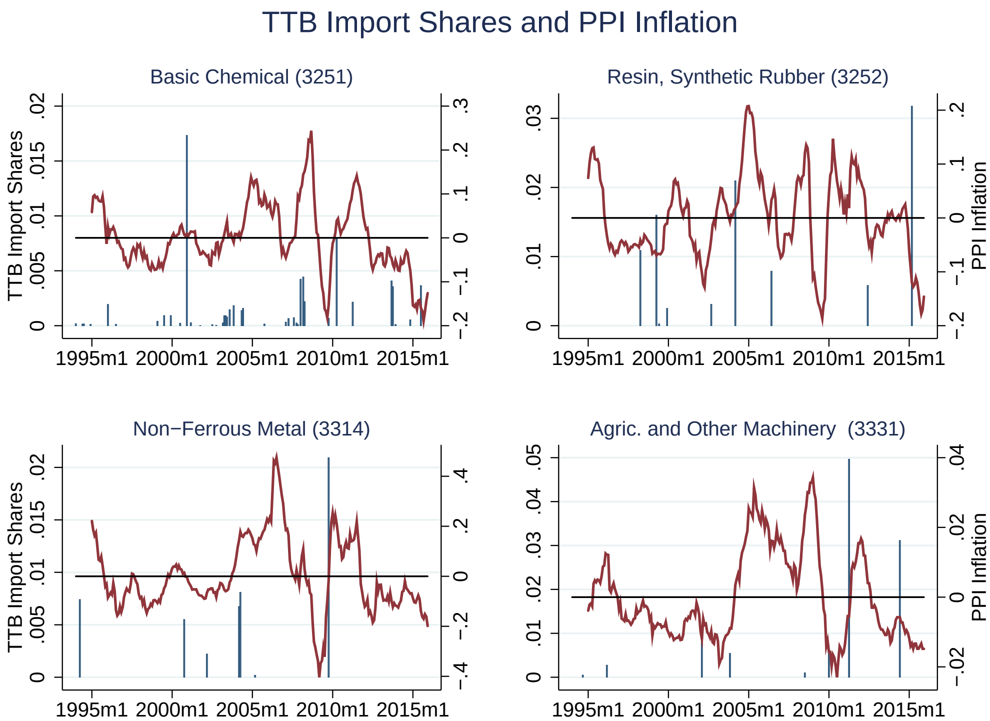

Figure A.3. Share of imports affected by TTBs investigations in selected NAICS-4 industries (histograms) and producer price inflation (continuous line).

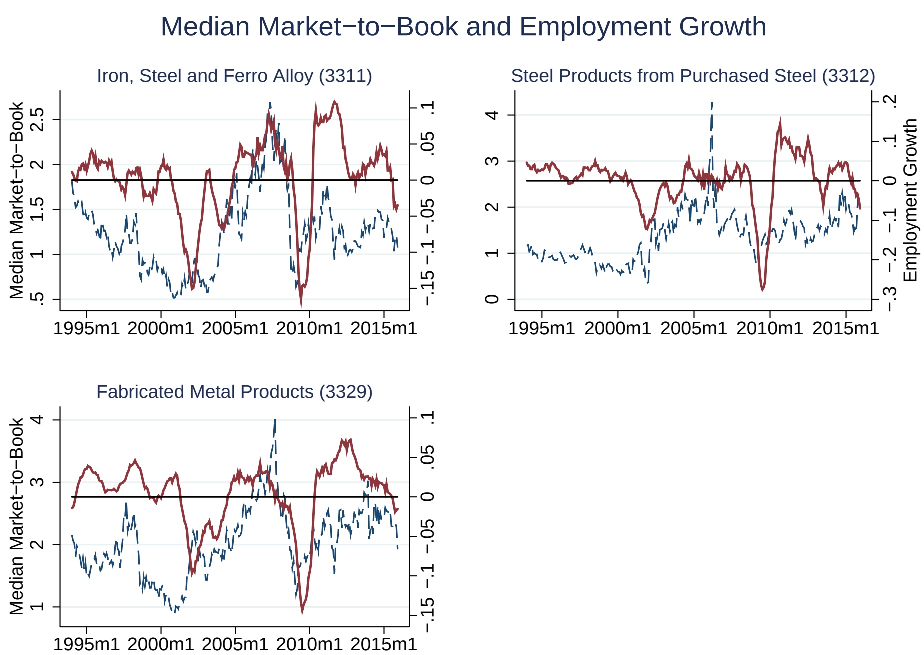

Figure A.4. Market-to-book ratio in selected NAICS-4 industries (dashed line) and employment growth (continuos line).

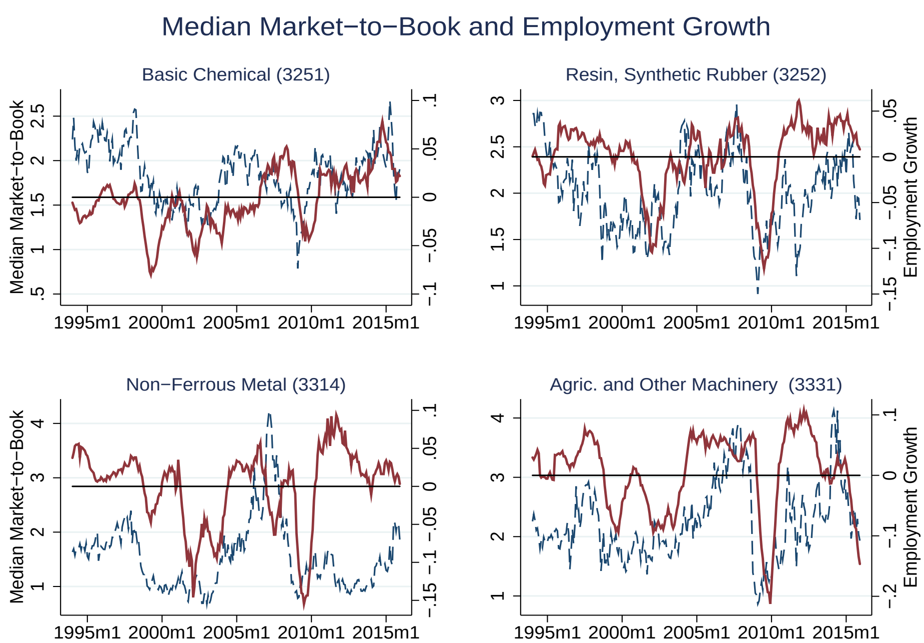

Figure A.5. Market-to-book ratio in selected NAICS-4 industries (dashed line) and employment growth (continuos line).

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

Dep. Variable: ΔL_t	Industry NAICS-4						
	3311	3251	3329	3312	3252	3314	3331
M/B_{t-1}	0.013***	0.008**	0.004*	0.002	-0.001	0.003	0.006**
	(0.005)	(0.003)	(0.002)	(0.004)	(0.003)	(0.004)	(0.002)
M/B_{t-2}	-0.005	-0.006	0.001	-0.005	0.000	-0.001	-0.001
	(0.007)	(0.004)	(0.003)	(0.005)	(0.004)	(0.005)	(0.003)
M/B_{t-3}	-0.001	0.001	-0.003	0.004	0.004	-0.000	-0.001
	(0.005)	(0.003)	(0.002)	(0.004)	(0.003)	(0.004)	(0.002)
ΔL_{t-1}	1.187***	0.899***	1.198***	1.092***	1.147***	0.955***	1.197***
	(0.064)	(0.062)	(0.064)	(0.064)	(0.063)	(0.063)	(0.063)
ΔL_{t-2}	-0.089	0.185**	0.106	0.147	-0.280***	0.151*	0.030
	(0.098)	(0.084)	(0.099)	(0.093)	(0.096)	(0.086)	(0.099)
ΔL_{t-3}	-0.116	0.044	-0.195*	-0.138	0.161	0.039	-0.193**
	(0.098)	(0.084)	(0.099)	(0.093)	(0.098)	(0.087)	(0.098)
ΔL_{t-4}	0.070	-0.030	-0.148	-0.203**	-0.112	-0.017	-0.077
	(0.100)	(0.084)	(0.098)	(0.094)	(0.098)	(0.087)	(0.099)
ΔL_{t-5}	-0.103	-0.040	0.049	0.078	0.131	-0.077	0.029
	(0.102)	(0.085)	(0.099)	(0.094)	(0.098)	(0.087)	(0.100)
ΔL_{t-6}	-0.109	-0.041	-0.059	-0.078	-0.034	-0.100	0.031
	(0.101)	(0.085)	(0.098)	(0.094)	(0.098)	(0.086)	(0.099)
ΔL_{t-7}	0.175*	-0.123	0.067	0.208**	-0.032	-0.069	-0.103
	(0.102)	(0.085)	(0.097)	(0.096)	(0.098)	(0.086)	(0.098)
ΔL_{t-8}	-0.021	-0.095	0.081	-0.114	0.070	0.063	0.135
	(0.102)	(0.085)	(0.097)	(0.098)	(0.097)	(0.086)	(0.095)
ΔL_{t-9}	-0.122	0.039	-0.279***	-0.076	-0.069	-0.096	-0.087
	(0.104)	(0.085)	(0.098)	(0.096)	(0.097)	(0.087)	(0.093)
ΔL_{t-10}	0.074	0.159*	0.017	-0.177*	-0.027	-0.004	-0.131
	(0.105)	(0.085)	(0.101)	(0.094)	(0.097)	(0.087)	(0.093)
ΔL_{t-11}	-0.103	0.143*	0.148	0.241**	-0.068	0.229***	0.150
	(0.104)	(0.084)	(0.101)	(0.095)	(0.096)	(0.086)	(0.093)
ΔL_{t-12}	0.067	-0.205***	-0.018	-0.054	0.022	-0.143**	-0.047
	(0.064)	(0.062)	(0.064)	(0.064)	(0.063)	(0.063)	(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
ΔL_{t-1}	-0.133	-0.010	-0.037	-0.078	-0.248***	-0.899*	-0.036	0.153***	-0.098**
	(0.100)	(0.011)	(0.106)	(0.085)	(0.067)	(0.464)	(0.022)	(0.005)	(0.047)
ΔL_{t-2}	-0.100	-0.000	-0.124	0.004	0.169	-0.581*	-0.022	-0.003	-0.034
	(0.102)	(0.010)	(0.100)	(0.027)	(0.109)	(0.320)	(0.051)	(0.005)	(0.047)
ΔL_{t-3}	0.002	0.023	-0.391***	0.017	0.243**	0.160	0.086**	0.034***	-0.012
	(0.100)	(0.016)	(0.114)	(0.049)	(0.107)	(0.161)	(0.044)	(0.006)	(0.047)
ΔL_{t-4}	-0.267**	0.016	0.253**	-0.060	0.050	0.315	-0.004	-0.203***	-0.003
	(0.129)	(0.011)	(0.101)	(0.073)	(0.100)	(0.287)	(0.022)	(0.010)	(0.047)
ΔL_{t-5}	0.063	-0.013	0.098*	-0.061	-0.284***	-0.259	-0.060	0.269***	-0.004
	(0.102)	(0.010)	(0.052)	(0.051)	(0.108)	(0.178)	(0.041)	(0.008)	(0.047)
ΔL_{t-6}	0.148	-0.015	-0.304**	-0.318*	0.074	-0.357*	-0.042**	-0.046***	-0.047
	(0.100)	(0.014)	(0.122)	(0.164)	(0.225)	(0.214)	(0.019)	(0.007)	(0.047)
ΔL_{t-7}	-0.030	0.025*	0.033	0.050	-0.233***	-0.080	-0.025**	-0.065***	-0.015
	(0.102)	(0.014)	(0.089)	(0.038)	(0.089)	(0.194)	(0.012)	(0.007)	(0.048)
ΔL_{t-8}	-0.072	-0.012	0.099	0.034	-0.128	-0.166	-0.029	-0.208***	-0.010
	(0.123)	(0.012)	(0.099)	(0.048)	(0.155)	(0.222)	(0.021)	(0.009)	(0.048)
ΔL_{t-9}	-0.040	0.017	0.020	0.111**	-0.063	0.243	0.068	-0.027***	0.077
	(0.135)	(0.014)	(0.088)	(0.055)	(0.215)	(0.167)	(0.052)	(0.004)	(0.048)
ΔL_{t-10}	-0.062	-0.009	-0.162**	-0.244	0.071	-0.185	0.000	-0.010*	-0.087*
	(0.087)	(0.021)	(0.066)	(0.211)	(0.072)	(0.199)	(0.019)	(0.005)	(0.048)
ΔL_{t-11}	0.077	-0.002	0.116*	-0.010	0.165	0.394	0.040***	0.062***	0.047
	(0.127)	(0.026)	(0.065)	(0.042)	(0.114)	(0.279)	(0.014)	(0.003)	(0.048)
ΔL_{t-12}	-0.131	0.003	-0.113***	0.204*	0.292**	-0.117	-0.069**	-0.086***	-0.047
	(0.122)	(0.008)	(0.037)	(0.104)	(0.141)	(0.130)	(0.035)	(0.005)	(0.048)
M/B_{t-1}	-0.006	-0.001	-0.000	0.002**		-0.006	-0.001**	0.011***	-0.002
	(0.007)	(0.000)	(0.001)	(0.001)		(0.005)	(0.000)	(0.000)	(0.002)
M/B_{t-2}	0.008	0.001	0.004**	-0.002		0.012	0.001**	-0.017***	0.003
	(0.009)	(0.001)	(0.002)	(0.003)		(0.011)	(0.001)	(0.001)	(0.002)
M/B_{t-3}	-0.007	-0.001	-0.003*	-0.000		-0.007	0.001**	0.005***	-0.002
	(0.005)	(0.001)	(0.002)	(0.002)		(0.010)	(0.000)	(0.000)	(0.002)
ΔP_{t-1}	0.020	-0.000	0.249***	-0.072*	0.251*	0.054	0.113*	0.025***	0.014
	(0.034)	(0.005)	(0.074)	(0.039)	(0.132)	(0.157)	(0.061)	(0.003)	(0.023)
ΔP_{t-2}	-0.014	0.009	-0.184	0.017	-0.444*	0.302**	0.001	0.081***	-0.035
	(0.066)	(0.008)	(0.191)	(0.044)	(0.249)	(0.152)	(0.197)	(0.003)	(0.024)
ΔP_{t-3}	-0.041	-0.001	-0.406***	-0.028	-0.900***	-0.208	-0.034	-0.072***	-0.021
	(0.048)	(0.003)	(0.116)	(0.023)	(0.279)	(0.148)	(0.059)	(0.003)	(0.023)
ΔL^{IO}_{t-3}	0.312*	0.022	0.121***	0.202**	0.007	0.986*	0.017	-0.206***	0.037
	(0.182)	(0.018)	(0.044)	(0.085)	(0.081)	(0.523)	(0.012)	(0.020)	(0.069)
ΔL^{IO}_{t-3}	0.538***	0.023	0.039	-0.002	0.047	1.207	-0.022	-0.682***	-0.002
	(0.182)	(0.022)	(0.084)	(0.067)	(0.086)	(1.102)	(0.042)	(0.024)	(0.070)
ΔL^{IO}_{t-3}	-0.432***	-0.017	0.090*	0.275	0.039	-0.064	-0.005	1.251***	0.030
	(0.129)	(0.016)	(0.052)	(0.225)	(0.105)	(0.706)	(0.020)	(0.033)	(0.070)
Aggregate Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Time and Industry FE	No	No	No	No	No	No	No	No	Yes